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Guiding principles for modelling-based papers published in *Futures*

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A R T I C L E I N F O

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A B S T R A C T

This article offers a critical reflection on the role of mathematical modelling in futures studies. It is written by members of the Futures editorial team and intended to guide authors interested in submitting papers on the formal modelling of futures to the journal. While models are increasingly prominent in shaping visions of the future across science, policy, and society, their use raises fundamental concerns. The paper outlines three key challenges: the limitations of models in handling novelty and surprise, their counter-performative effects in shaping rather than simply anticipating futures, and the epistemological consequences of their dominance in evidence-based policymaking. Drawing on critiques from science and technology studies, economics, and complexity theory, the authors argue for a more reflexive, inclusive, and pluralistic approach to modelling. They propose six guiding principles—transparency, reflexivity, inclusivity, complexity (not complicatedness), relevance over precision, and contribution—to guide submissions to Futures. The goal is to ensure that modelling contributes meaningfully to the field's core mission: the collective construction of better futures, and to help authors in writing papers that are appropriately reflexive towards the use of models in futures work.

1. Introduction

Models, in the sense of abstract representations, have been part of how we make sense of the world and what may happen in it throughout human history. Within the natural sciences, models and modelling have been central to knowledge production since at least the nineteenth century (Suárez et al., 2024). But at present, modelling plays a particularly prominent role in producing and legitimising alternative futures. This is evident in the many submissions to this journal and in the increasing emphasis on modelling across the disparate fields and domains it addresses. In this paper, we reflect on the relationship between futures studies and modelling and consider some general concerns underlying the use of models in futures studies. The authors are members of the editorial team for *Futures*, and our reflections here are intended to serve a practical purpose, helping guide authors and inform editorial decisions.

By 'modelling' we refer particularly to the representation of possible future realities, a) by encoding relationships between variables, whether empirically derived or otherwise (as in, for example, statistical, mathematical and econometric modelling), and b) by means of the emergent outcome from modelled interactions between cases (as in, for example, agent-based modelling). This is not an

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all-encompassing definition. We are not, in this paper, concerned with the more general senses in which models might be used to describe desired futures, as for example in descriptions of ‘model behaviour’, or in the role played by future images in theories of anticipation or agency, though both these senses have been the topic of many contributions to the journal. The formal models employed in philosophy are similarly not our concern here. The kinds of models and modelling we have in mind in this article are those varieties of formal modelling mentioned above, and in particular applications of these models that rely on large amounts of quantitative data to offer probabilistic accounts of possible futures: we will, for convenience, call this ‘mathematical modelling’ in this paper. Our focus on mathematical modelling might also raise, for readers, broader philosophical questions about the nature of measurement in a field that focuses on something that does not exist empirically (the future), or questions about the application of models within ‘big data’ and artificial intelligence, two topics regularly discussed within *Futures* for a variety of reasons. But these broader areas are not the primary concern of this paper, though they may arise in one or two places when discussing a specific issue.

Our focus on the relationship between mathematical modelling and futures arises from two considerations: first, the effects of this kind of modelling on how ideas about the future are mobilised in society. And second, the practical use of this kind of modelling in furthering the aims of futures studies generally, and of this journal specifically.

In the next section, we establish the need to reinitiate what is already a long-standing discussion on the role of modelling in futures studies, describing some contemporary features of modelling that illustrate the uneasy relationship between modelling and futures studies, and in each case suggesting some considerations for authors exploring the relationship between modelling and the future. In section three, we engage with recent critique from related fields that offer a useful perspective on how models are used to produce ideas of the future and the assumptions often made about their application. This section presents an illustrative example of just such a critical perspective in considering the degree to which complexity is imagined as a desirable attribute of models. Section four summarises the value to futures studies of engaging with modelling as a way of producing ideas of the future and sets out our recommendations for authors wishing to contribute accounts of work using modelling to *Futures*. The concluding section outlines our manifesto for a modelling approach that can contribute to the central objective of futures studies: the betterment of future society.

2. Reinitiating the discussion on the role of modelling in futures studies: why now?

There are three principal concerns that make it timely to reinitiate a discussion on the role of modelling within futures studies. First, concerns about the capacity of modelling to anticipate novelty in open systems; second, regarding the ‘counter-performativity’ of models; and third, relating to the place models and modelling occupy within contemporary discourses of policy and evidence. These are described in the subsections below, along with some discussion of the implications of each concern for researchers writing about models and the future.

2.1. Novelty and surprise

Events continue to demonstrate that, despite their increasing sophistication, little progress has been made in using modelling to anticipate highly impactful surprises. Events such as the 2007-08 financial crisis and the coronavirus pandemic should not have come as a surprise to public policy teams or politicians, but nevertheless did. While mathematical modelling is not the only way public policy groups try to anticipate emerging risks, these events illustrate a fundamental problem with models: they are constructed to represent what is known at the expense of what is unknown, from which surprises arise. As the systems thinker John Sterman puts it, ‘The most important assumptions of a model are not in the equations, but what’s not in them; not in the documentation, but unstated; not in the variables on the computer screen, but in the blank spaces around them’ (Raworth, 2022, p.66).

Surprises, therefore, arise in part from a lack of attention given to what G. L. S. Shackle called ‘unknowledge’ (Metcalfe et al., 2021) and what Taleb (2008) called ‘Black Swans’. Discussions of surprise are part of long-standing debates about uncertainty, which gave rise to post-normal science (Funtowicz & Ravetz, 1993) and have been central to debates in science and technology studies (STS) about the limitations of expert perspectives in the face of uncertainty (Wynne, 1992). Modelling, when undertaken naively, exacerbates this problem of limited perspectives, increasing susceptibility to surprises (Derbyshire and Aven, 2025; Derbyshire, 2022). Crises, notwithstanding their capacity to usher in transformational change (Anderson, 2010), are generally better avoided. But modelling that is limited through a preference for knowledge established through expert consensus makes it harder to anticipate them. Futures studies can play a role in combining modelling with more qualitative ways of knowing, imagining and understanding, which have greater capacity for working with openness, novelty, emergence and transformation. For reasons we explore later in this paper, in most of its forms, variance-based modelling will always be very limited in its ability to account for these fundamental features of reality (Cox, 2020).

Models inevitably frame reality in a way that emphasises some of its more directly observable aspects at the expense of others that may be less directly observable, yet more important. This framing of the observed reality can cause some of its more latent but important aspects to be overlooked, and that not only has implications for anticipation (or the lack of it), but relatedly, also for justice, equality, diversity, and inclusion, which this journal has a long tradition of promoting. And the two are closely related because equality, diversity, and inclusion are highly important for avoiding surprises (Mitchell & Chaudhury, 2020). We all have blind spots that reflect the unique circumstances and experiences associated with our background, education, culture and race. None of us is neutral, and none of us has a ‘God’s eye’ view capable of reaching complete knowledge.

Variance-based models require stability to guide exploration of alternative futures, yet the world is constantly changing. Variance can only ever be measured from past outturns and so its use, by definition, embeds exploration of the future in the past, thus greatly constraining the range of future possibilities explored. These problems manifest in the obscure yet important assumptions of ergodicity and stationarity in variance-based models. The assumption of ergodicity implies that a system will visit every part of its state space over time. In contrast, many systems of interest to futures scholars instead exhibit path dependence, in which future possibilities are constrained by past states, meaning some states comprising what would otherwise be the system's state space can never be visited.[1] The assumption of stationarity implies that a timeseries has constant characteristics over time, as manifest in a stable mean, variance and autocorrelation structure.[2] Awareness of these assumptions is very important for any futures scholar, but they have received relatively little explicit discussion in this journal. While perhaps preferable because it does not depend on such assumptions, even the use of a case-based rather than a variance-based approach to modelling cannot fully account for openness, novelty, emergence, and transformation over time. An agent-based model, for example, still requires agents' interactions to be governed by a set of programmed rules. This means it, too, has a limited ability to account for the human reflexivity that is a primary cause of nonergodicity and non-stationarity.

Only by drawing deeply from the well of diversity can blind spots be avoided and a wider range of potential surprises be anticipated, though inevitably some will still blindside us. This diversity encompasses methodological diversity, which resists placing any one approach or method on a scientific pedestal above others, alongside epistemological diversity, so that the views of those who do not use modelling-based approaches to exploring futures are not somehow downgraded or diminished in importance. Epistemological diversity (in addition to concerns about epistemic justice) requires that the voices of those from marginalised and discriminated communities, low-income groups with less access to formal education, who may be less well versed in modelling and its strictures, are not diminished or downplayed because their arguments are not couched in the technocratic language of modelling. The idea of extended peer communities put forward by post-normal science (Funtowicz and Ravetz, 1990; Funtowicz and Ravetz, 1993) is precisely an argument for epistemological pluralism.

2.1.1. Implications for authors

Modelling is just one tool in the futurists' toolkit and might be very constraining when used to the exclusion of the others, or when considered to offer a higher level of scientific input. The future can look very different depending on the lens through which one views it, and modelling is just one such lens—albeit one that comes in a wide range of curvatures, each refracting light in different ways, each bringing into focus some aspects of the future at the expense of others. We feel there may be significant, largely unexplored scope for combining modelling with other futures tools to provide a more holistic and rounded view of the future (Beard et al., 2020). Only by combining mathematical modelling with different approaches to exploring futures can we hope to account for openness, novelty, emergence and transformation over time in anything like an adequate way. That is an agenda we want to promote through this paper.

2.2. Counter-performativity: self-fulfilling prophecies and the interests of model creators

Modelling-based considerations of the future were centre stage during the coronavirus pandemic and were reported daily in newspapers, broadcast media, and disseminated through social media. The social impacts of using models were thus hugely significant. Researchers in STS often study how the outputs of models have a transformative effect in the present, through the self-altering, self-fulfilling and self-denying nature of anticipation (Patomäki, 2019). For example, scenarios suggesting the rapid spread of coronavirus in the absence of checks were used to justify strict quarantines, which then curtailed the virus's spread, prevented the scenarios from being realised, and helped to solidify the governance of the pandemic.

This 'counter-performative' role for modelling (Thompson, 2022), in which the use of a model is designed to stimulate actions that alter, fulfil or prevent the anticipations derived from it, is not something new. Models have always been used to bolster arguments promoting specific courses of action that alter the future.[3] As scholars in STS and the sociology of expectations have shown, the use of models as visions of potential futures (Reichmann, 2013) can create consensus about future possibilities and, with these, support the

[1] The assumption of ergodicity is important for many forms of modelling (and especially econometric modelling). It essentially denies the constraints on the future that result from the past, which is important because many futures scholars are interested in how future possibilities can be broadened out to include those that are positively transformative for society. Rather than freeing up exploration of the future by untethering it from the constraints of the past, by denying path-dependence, models that assume ergodicity fail to grapple with the past's institutional and behavioural legacy. This means that matters related to power, agency and politics are inadequately dealt with, thereby inhibiting rather than enabling the consideration of alternative and transformational futures. See Section 3 for further discussion.

[2] In a stationary timeseries, because of this stability, these values do not depend on when the timeseries was observed. If we imagine a timeseries stretching back 200 years, stationarity would mean that any parameter values estimated from a partial 50-year timeseries taken from it would be more-or-less the same as those estimated from a different partial 50-year timeseries also taken from it. In reality, of course, change happens–either endogenously or exogenously, or both—and disrupts the estimated parameter relations, meaning these values would be quite different when estimated over the two distinct 50-year periods. This has obvious implications for consideration of the future as a model employing parameters estimated using one of these 50-year periods would produce different projections into the future than those produced by a model employing the other 50-year period for parameter estimation. Granted, futures studies is about exploring alternative futures rather than forecasting the future accurately (for which non-stationarity is a pretty much fatal problem), but non-stationarity nevertheless brings into question the usefulness and purpose of using variance-based modelling in futures studies. See Section 3 for further discussion.

[3] This is not least because modelling is central to the production of evidence, which is one of the elements that inform policymaking, and policies have the explicit purpose of changing an aspect of reality. This means that a new policy is essentially designed to bring about change, leading to instability, whereas most forms of modelling used in policy-making require stability to prove useful as a guide to the futures that may ensue from a change in policy (Derbyshire, 2020). This underlines the inherent tension within the very idea of modelling as a way of 'knowing the future'.

activities of coalitions of actors. This is one reason why it is inappropriate to present modelling as necessarily neutral and 'objective', and why prediction ought not to be imagined as its primary purpose.[4] It is also a reason why modelling has the potential to play a central role in futures studies, which is as much about creating the future we collectively want as it is about considering what might happen.

The wider significance and impact of such counter-performative modelling are arguably most evident in relation to issues such as climate change. Scientists modelling the climate and the impacts of changes in global average temperatures (e.g. through Integrated Assessment Modelling) do so to understand them and their potential futures. One purpose of these activities is to understand how specific policy interventions might affect the climate by reducing carbon emissions to varying degrees. Essentially, this modelling assists in creating new policies to prevent the potential extremes these models envisage under a 'business-as-usual' scenario. The effectiveness of alternative policy combinations is simulated to understand the mix of policies and actions that would reduce carbon emissions sufficiently to meet climate targets, which will not be met if we continue as we do now. We might consider this a positive and beneficial use of the counter-performativity of models.

Climate change also demonstrates the dangers of counter-performative modelling, especially in how it may affect behaviour in unexpected, counterproductive ways. For example, recently, a group of prominent scientists conducted extensive research to better quantify the range of global warming by estimating the climate's sensitivity more accurately (Sherwood et al., 2020). They no doubt had good intentions, as they considered reducing uncertainty about global heating beneficial for stimulating governments and individuals to take actions to mitigate it. Yet, the very act of attempting to bound the extent of heating with greater certainty has the potential to be counterproductive, making the upper bound of the newly estimated range of global heating appear more unbreachable than it really is (Derbyshire & Morgan, 2022). It frames climate change in a way that might discourage individual and collective mitigating actions rather than encouraging them (Derbyshire & Morgan, 2022). The reflexivity that counter-performativity stimulates (i.e. changes induced in human behaviour) can therefore lead to unintended as well as intended alterations to the future, exactly as Patomäki (2019) suggests.[5]

Futures studies may well be about anticipating alternative futures, but, as we have noted repeatedly here, it is also about constructing collectively desirable futures. This introduces a circularity that is problematic for many mainstream forms of modelling, as described by the 'Lucas critique' (Lucas, 1972; Lucas, 1976) of econometric modelling and Leamer's (1983) similar critique of the 'con' in econometrics. Lucas recognised that a new policy based on econometric modelling can disrupt the stability of the present situation on which the modelling was based (Derbyshire, 2020). Or the policy might ensure the actualisation of the model's envisaged outcome when it would not otherwise have occurred. Essentially, the policy alters the underlying structure of what the model was designed to reflect, meaning the parameter relationships it captures are no longer valid, and its coefficients are disrupted. The model's parameter relations reflect what has happened in the past, but the policy disrupts them, meaning that which future then transpires is uncertain. This reflects a fundamental truism in relation to almost all forms of modelling: they require that reality remains stable to be useful as aids to anticipating the future, but the purpose of modelling is precisely to justify interventions which then disrupt the future as modelled and create new uncertainties.

Gigerenzer (2022) discusses this problem of instability in detail, describing how almost all forms of data analysis and modelling assume stability that is rarely present in most systems of interest. This problem becomes particularly acute when models are used for counter-performative purposes, as they often are in our domain. As we have discussed, and as was evident in the pandemic, scenarios produced through modelling are used not to predict the future but to alter it. As applied more broadly to our domain, this problem stems in part from our attempt to change the future rather than merely passively anticipate it.

Essentially, this means those researching and practising in futures studies are purveyors of non-stationarity and nonergodicity. Many attempts have been made to solve the problems of nonergodicity and non-stationarity in modelling over many decades, but most can be considered mere technical sophistication as camouflage (Nasir & Morgan, 2018), which nod in the direction of the problem without genuinely grappling with its ontological implications. These 'solutions' provide the dressing needed to sustain the use of modelling approaches that simply cannot deal with the nature of change in an open, complex and emergent world.

There is much that could be said here about probability theory and its application to the consideration of the future. What is disrupted and made unstable by the underlying changes to reality induced by a new policy or course of action (e.g. social distancing in the pandemic) are the assumptions regarding the nature and functional form of the probabilistic relationship between modelled variables. Whether explicitly or implicitly, the problems of nonergodicity and non-stationarity have prompted researchers and

[4] Patomäki (2019) examines this and related matters in a book chapter on the reflexivity of anticipation that is very pertinent to the present discussion. In it he distinguishes between self-altering, self-fulfilling and self-denying predictions. As Patomäki (2019, p.17) correctly states, 'anticipations tend to become an integral part of the situation and thus affect subsequent developments…'. For this reason, predictive accuracy is often not their purpose and so cannot be the basis of their evaluation. As Patomäki also comments 'Self-altering predictions can move the world into a direction that may or may not be desirable' (Patomäki, 2019, p.17), which is one of the primary concerns motivating the writing of this paper. The self-altering, self-negating and self-fulfilling nature of anticipations raises fundamental questions when it comes to the evaluation of the tools and methods used in futures studies (see Derbyshire et al. 2023). If they are designed to alter the future rather than predict it, then predictive accuracy is not the measure by which their usefulness should be assessed.

[5] This reflexivity was also evident in the coronavirus pandemic in the alternative measures of the Basic Reproductive Number (R0) that were employed to influence policymaking that would affect the Effective Reproductive Number (R). This was a classic example of 'Goodhart's Law' in action, the central implication of which is that a new indicator or measure, once created and deemed important, diverges from its relationship with reality from then on because of the reflexivity it has induced (Derbyshire, 2020; Goodhart, 1981; Patomäki, 2019).

practitioners in the field of futures to focus on plausibility as a criterion for the usefulness of scenarios and model outputs more generally rather than on probability (Ramírez & Selin, 2014). But doing so may simply transform the problem from a technical one into one of legitimacy.

There is much that could be said at this point about whether the use of Artificial Intelligence can assist in overcoming the problems associated with modelling we have discussed thus far, or whether its use might in fact exacerbate those problems.[6] However, while this is a prominent and important topic, it is not the central concern of this editorial.

2.2.1. Implications for authors

Because models tend to play a counter-performative role, it is important to ensure those publishing modelling-based papers in this journal are transparent in their motivations–i.e., that they do not hide behind the appearance of scientific rigour (Saltelli et al., 2013) in order to promote particular agendas, and instead explicitly recognise the inherent tensions in the idea of modelling as 'knowledge of the future'. It is also important that they consider how counter-performativity may backfire by stimulating reflexive responses that lead to unintended changes in human behaviour, thereby inhibiting rather than advancing desirable futures.

Reflection on i) what preferred futures are at least implicit in modelling, ii) who may prefer them, and iii) why they may be preferred is key to ensuring the powerful counter-performativity effect of models is used to change the future for the better, not the worse. This raises important questions about legitimacy, expertise, and reflexivity that cannot be brushed aside. Even a pressing problem like climate change may be captured by vested interests in the form of stakeholders who seek to employ the counter-performativity of models to steer the unfolding future in a direction advantageous to them, rather than to broader society. For example, the gas-boiler lobby in the United Kingdom have used models extensively to stymie the diffusion of heat pumps, slowing one of the most important technology transitions needed for that country to meet its net-zero targets (Derbyshire, 2024). The prevalence and power of modelling's performativity are a strong motivation for reinitiating a discussion of modelling and futures.

2.3. Wider culture of evidence-based policy design

Since the nineteenth-century adoption of statistics as a mode of understanding society and the state (Porter, 2020), public policy has derived legitimacy from its engagement with research and evidence. Today, recent ideological turns within authoritarian states notwithstanding, governments around the world continue to place importance on using evidence to inform policy development, and this often results in greater use of modelling to anticipate outcomes and justify one course of action over another. Any new policy is a statement about a desirable future. Yet there is much that is unknown, and perhaps even unknowable, about whichever future follows from a new policy (Pawson et al., 2011). Evidence-based policymaking places the measurable—and therefore the modellable — on a pedestal, not only relegating other forms of knowledge to second-class status but also, in the process, constraining the possibility of the more radical transformation now needed to solve many societal problems.

For example, the UK Treasury's official 'Green' and 'Magenta' policy-evaluation handbooks emphasise the use of randomised controlled trials, cost-benefit analyses, and other data-driven 'rational' approaches to considering the futures that may emerge from a new policy. These approaches are a high hurdle that potential policies must overcome in their *ex-ante* evaluations to be implemented. Yet, such 'rational' approaches to decision-making based on Expected Utility Theory—cost-benefit analysis being the best example–have only limited means by which to account for the irreversibility and potentially incalculable ruin that feature prominently in relation to pressing societal problems like climate change, but also in relation to something like a pandemic (Aldred, 2010). They frame the observed reality in only one way and accept the central tenet of Rational Choice Theory, which is that allowing one's outcome preference to influence one's action preferences is irrational (Derbyshire, 2024). In contrast to that view, diverse stakeholders may frame the future in ways that are sometimes incommensurable and argue for outcomes they prefer on the basis of non-fungible values, which is perfectly natural. As a society, we prefer to avoid extreme climate change, and the incalculable and irreplaceable losses it would likely entail, and it is entirely appropriate that our considerations of the future should be 'biased' towards that end.

Furthermore, approaches based on Rational Choice Theory (RCT) leave little room for the structured acts of imagination that can identify truly transformational futures. True rationality is not merely a matter of optimising known possibilities; it is about generating new possibilities, better options, and improved outcomes. It is about expanding knowledge into the domain of the presently unknown to generate novel possibilities that might lead to betterment (Gilain et al., 2023; Le Masson et al., 2019). Yet, the restricted 'rationality' of RCT-based approaches, which promote the optimisation of a limited set of known possibilities, is the standard to which one must

[6] For instance, in a paper that futures scholars can glean many insights from, Cox (2020) comments about the adjacent field of risk analysis that 'Standard decision and risk analysis questions become inherently unanswerable ('undecidable') for realistically complex causal systems with 'open-world' uncertainties about what exists, what can happen, what other agents know, and how they will act'. Although Cox (2020) goes on to discuss how recent advances in artificial intelligence *can* assist in overcoming this problem, the allusion to questions being 'undecidable' is a reference to Alan Turing's concept of 'undecidability', which implies, roughly speaking, the impossibility of knowing whether a future state of the world can be reached from a present state of the world, and what the probability of reaching it is. Indeed, to tie this more directly to our present concerns, Turing (1954) argued that undecidability implies that some problems are simply unamenable to resolution by mathematical approaches. For Cox (2020), the circumstances that make this impossible are those of 'open-world uncertainty', which arises from the tendency for reality to produce novelty. Greater computational sophistication and power can only assist in selecting from among paths into the future if the future can be closed and all its potential paths and their outcomes listed in the present. We, as futures scholars, know as well as anyone that this will never be possible, thus placing a limit on the extent to which artificial intelligence can assist in navigating towards desirable outcomes.

adhere if one wants to change government policymaking. These approaches imply that policy decisions should simply implement the course set by a science imagined to be accurate, correct, and free of values, although the role of 'evidence' in the policy development process is complex (Parkhurst, 2016). As many have pointed out (Gorski, 2013; Laudan, 1984; Lekka-Kowalik, 2010), scientific practice and the facts it produces are not free of values, and the distinction between science and policy is not absolute, with each playing a role in constituting the other (Saltelli & Giampietro, 2017).

We agree with Bermúdez (2020) that, in the face of great uncertainty, what is now needed are new tools for rational decision-making that recognise human rationality as the multifaceted thing it really is. For example, humans use narratives of various kinds to frame consideration of the future and to make decisions that foreground one outcome over another. Doing so is not irrational in the way behavioural and mainstream economics would imply (Derbyshire, 2024). Indeed, a multifaceted consideration of narratives is necessary for robust reflection on the future. We feel that the futures field can already offer many of the tools needed for such an approach to rational decision-making, which Bermúdez (2009, 2020, 2022) has consistently argued for. But their adoption requires that formal, mathematical modelling and the use of the models it produces are reframed so that they are seen as just one component of a holistic consideration of the future.

This point raises questions about which kinds of expertise are relevant to futures thinking. The question of who has expertise—central also to post-normal science—easily morphs into a related one about who it is that gets to decide what a desirable future is, which is in turn related to post-normal science's call for extended peer communities. During the coronavirus pandemic, the harm from allowing the virus to spread was deemed worse than the harm resulting from the measures taken to prevent its spread. Yet inevitably, some considered the opposite more likely, based on factors harder to model but perhaps highly consequential (Anderson, 2021). Models can have ritual value that affirms some groups' norms, but, in doing so, can exclude certain groups and futures (Wynne, 2010). That may also be true of plausibility-based approaches, which inevitably require that experts be put on a pedestal to determine what is plausible and what is not. The International Panel on Climate Change is one such expert group, along with others that featured in pandemic decision-making, such as the UK Scientific Advisory Group for Emergencies (SAGE).

One obvious implication of the foregoing reflections is that the assumptions on which a model is based must be stated clearly, and must be transparent and easily understood (Gigerenzer, 2022), but is that enough, by itself? The importance of hidden assumptions has not only been highlighted by Peters (2019) research on the important ergodicity assumption that sits behind much modelling as discussed above but also by Taleb's (2020) related research on the 'hidden moments' of the fat-tailed probability density functions that describe many of the highly consequential and extreme events that might be of concern to scholars in futures studies. An empirically observed mean that is, for example, calculated from an available time-series stretching back fifty years, will differ from the mean that would be calculated from an infinite time-series, if it were ever possible to collect one. The mean from the infinite time-series is therefore a hidden moment, and its difference from the unhidden, calculated mean could be very significant. The same is true for other moments, such as the maxima (i.e. the upper bound of a probability distribution's range) because the most extreme possible instance of a given variable that could occur over infinite time is unlikely to be contained within the time series one has, meaning its use for considering the future will downplay the potential for extreme outcomes. This suggests that models that incorrectly assume certain functional forms are not only of little use to consideration of the future but are outright dangerous because they underplay the likelihood (or, if we prefer, plausibility) of extreme outcomes.

While the pandemic may have greatly increased the prominence of modelling-based considerations of the future, it also starkly revealed the many difficulties and dangers associated with them. Modelling arguably contributed to the failure to implement a strict quarantine sooner in the United Kingdom (Derbyshire & Aven, 2025). Divergent expert opinions on the spread of the virus, the measures to be taken, and the number of deaths, as well as uncertainty about the means of contagion and prevention, made it clear that science does not speak with one voice (Waltner-Toews et al., 2020).

2.3.1. Implications for authors

Modelling-based papers appearing in this journal should display sufficient reflexivity towards the possibility of a model being misleading or detrimental to its intended purpose, or under what circumstances the modelling might have undesirable side-effects. This reflexivity should also consider how models tend to both reflect what is already known (and thus blunt the possibility of anticipating surprises) and reflect implicit desired futures that help gain legitimacy for them at the expense of genuine robustness. Taking these possibilities into account reinforces the suggestion of Frigg and Smith (2022) that few, if any, systems of interest have the stability needed for their models' probability density functions to remain sufficiently stable over time to be an accurate guide to the system's possible futures. Models' predictive powers are necessarily limited, and authors need to communicate these limitations.

We recognise that modelling, in certain circumstances and domains, can be a transformative force for good. But when done badly, it can be used to prop up and defend the status quo and, even worse, to reverse progress already made. We want modelling that is published in this journal to be a force for good. We recognise, nonetheless, that 'good' may mean different things to different people, and that modelling alone cannot account for the plurality of legitimate values and perspectives in society. As we have already noted, Bermúdez (2020) seeks to reframe the meaning of 'rational' in decision-making, recognising that the current understanding of it harms more than it aids the fight against climate change.

We wish, through this paper, to position Futures as a venue for distinctive contributions and critical engagements from researchers associated with the important, still-nascent concepts and fields discussed in this section. *Futures* has supported post-normal science from its infancy (Kovacic & Biggeri, 2023), so it already has some pedigree in this regard. We also support the discussion and development of new perspectives and fields, such as critical data studies, but believe work remains to be done to flesh out exactly what is meant by this in a field such as futures studies.

3. Engaging critically with the uses of modelling

Discussions about issues with modelling have gathered pace with recent publications such as *Escape from Model Land* (Thompson, 2022) that have bridged academic and popular literature, as well as more established work in critical data studies, within science and technology studies (e.g. Kitchin & Lauriault, 2014; Dalton & Thatcher, 2014; Gitelman, 2013; Boyd & Crawford, 2011), and recent thinking within sociology on the politics of quantification in research (e.g. Saltelli & Di Fiore, 2023; Espeland & Yung, 2019). It is the hope of the *Futures* editorial team that the journal might continue to host work contributing to these debates. But that requires that those publishing on these subjects are cognisant of the long-standing discussions in this journal that has already taken place and write in a way that engages with and adds to them, rather than merely using the journal as a vehicle for describing yet another model and its output in a way that is divorced from the existing discussion.

Work published in *Futures* that makes use of models or engages with their products ought to be aware of existing critique addressing the relationships between models and the future, and the impact of these relationships on wider social life, such as the consequences of using actuarial methods in judicial decision-making (Harcourt, 2006), or the tendency for powerful actors to pre-emptively respond to projected risks (Amoore, 2013). It should avoid the 'naïve empiricism' with which correlations in models are treated, exemplified by Google Flu Trends, launched to much fanfare circa 2007 and alleged to do away with the need for theory when anticipating the future (Gigerenzer, 2022; Katsikopoulos et al., 2022). Its logic implied we could anticipate flu pandemics merely by examining empirical data on what people were searching for. Yet, Google Flu Trends was then quietly withdrawn circa 2015, when it was realised that it produced spurious correlations between words indicative of flu and completely unrelated matters, rendering it useless as an anticipatory aid (Gigerenzer, 2022).

When it comes to modelling, there is a view, perhaps also increasing in its prevalence, that increased modelling complexity automatically equates to increased accuracy, or at least, increased usefulness. For example, Mercure et al. (2016) debate whether higher or lower levels of complexity are better for climate models used in policymaking, suggesting that lower complexity does not necessarily equate to better science simply because it makes a model more understandable. But what they neglect to acknowledge is that the reverse is also true: increased complexity does not automatically equate to better science either. Moreover, Mercure et al.'s (2016) discussion on the subject skirts awfully close to conflating complicatedness with complexity. A very simple model can exhibit complexity, which relates to its ability to account for emergence that is irreducible to the aggregate of individual causes considered in isolation at a lower level of analysis (Derbyshire, 2016). Conversely, a very complicated model may be incapable of accounting for emergence and will therefore not be complex.

Complexity requires the use of multiple scales of analysis (Ahl & Allen, 1996; Kovacic, 2017; Zellmer et al., 2006) that capture both the local rules of interaction among system components and the emerging properties of the system as a whole. Multiple scales of analysis create non-equivalent descriptive domains (Kovacic & Giampietro, 2015; Rosen, 1985). Complex models that span over multiple descriptive domains are necessarily characterised by ambiguity (Kovacic & Di Felice, 2019), generating uncertainty rather than more accurate knowledge. In Katsikopoulos et al. (2022), regarding the Google Flu Trends example discussed above, it is shown that a very simple two-parameter model performs better than Google's many-parameter model at anticipating flu outbreaks. So, greater complicatedness in terms of more parameters and more data does not necessarily equate to increased usefulness.

Still more importantly, as Saltelli et al. (2020, p.483) have pointed out in a paper on modelling published in *Nature* (which was a source of inspiration for this contribution) '…many are seduced by the idea of adding complexity in an attempt to capture reality more accurately' in a way that leads to a key problem: overfitting. A better fit to the training data can reduce a model's ability to anticipate the future because it constrains the range of future possibilities too strictly—a matter closely related to the ergodicity and stationarity assumptions inherent to many forms of modelling.

We would argue that increased complicatedness is often conflated with an improved ability to take account of complexity, and relatedly, with increased accuracy. Whereas what it usually equates to is merely increased opacity. We suggest that accuracy is a dubious concept in a field that aims to offer a range of alternative perspectives on the future, rather than claiming simply to predict it. In the next section, we elaborate on some of the theoretical and philosophical points made in this section to clear the ground for what then follows: our guidelines for modelling-based considerations of the future published in this journal.

4. Making models serve the purpose of constructing better futures: recommendations for authors

The considerations outlined above, while not an exhaustive discussion of the relationship between modelling and futures studies, demonstrate that this relationship is not straightforward. They must be considered by authors who wish to publish modelling-based considerations of futures in this journal. The constructivism inherent to futures studies, as manifest in our affirmation that anticipation is never simply passive but always implies attempting to change the future for the better, somewhat complicates the role of modelling in our field compared to in, say, physics. Yet, even in physics models are *not* designed to be literal representations of reality. Even in physics the stability needed for systems to be predictable using models is rarely present (Frigg & Smith, 2022), yet models are still widely used in that discipline, and one cannot imagine a field of physics without them.

This firstly suggests models have useful purposes beyond prediction in marshalling thoughts and evidence, considering alternative or counterfactual outcomes, and explaining and understanding phenomena, all of which we need to consider in relation to their usefulness in the field of futures specifically. Secondly, and relatedly, it suggests that the impossibility and/or undesirability of prediction in relation to many matters of concern in futures studies is not in itself a reason to dismiss the use of models, which can have many other purposes. Thirdly, we can say that among these purposes, which models share with other tools employed in futures studies, is the provision of a means to articulate and explore one's possible assumptions about the future and what they mean for the present.

Without being clear about one's assumptions, how they were arrived at, and what other possibilities one might have adopted instead, a model has little if any value. Fourthly, models are not magic. Merely formalising and potentially quantifying one's assumptions about the future cannot produce objective empirical knowledge of it. The value of models as futures tools is greatly diminished when models are treated as if they offer objective predictions regarding what the future will be like.

In this final substantive section, based on the preceding discussion, we set out our guiding principles for modelling-based papers that seek to serve the purpose of creating better futures. As we are members of the editorial board of *Futures*, these guidelines are intended to guide authors and inform editorial decisions. Based on the preceding discussion, we suggest there are six principles on which those wishing to publish modelling-based considerations of the future should reflect.

1) Transparency: Modelling papers should be understandable, including by a non-expert audience, and should not contain hidden assumptions–e.g. those associated with ergodicity and stationarity. Modelling papers should consider all aspects of uncertainty, including but not limited to the methodological uncertainty associated with the model itself, and the possibility for irreversible and ruinous outcomes. They should consider the circumstances in which the model might be inadequate, and those in which the model might be misleading and detrimental to constructing a better future.
2) Reflexivity: Modelling papers should not solely describe a model and its output. They must reflect on the way the model and its use frames reality, inevitably drawing attention to some aspects of it and away from others and how using the model for practical (including policy) purposes may alter behaviour in a way that negates, alters or fulfils its anticipations. Both its performativity and counter-performativity need to be considered. Consideration must be given to how the modelling might define what 'desirable' changes are and how it takes into account (or perhaps does not) the plurality of legitimate perspectives within society regarding what constitutes ultimate ends.
3) Inclusivity: Variable-centred and variance-based models–because of their tendency to aggregate people and other entities (e.g. firms) into categories from which are derived variables that are then invested with a power to have effects that are independent of the entities from which they were measured—have limited ability to differentiate the distinctive effects of unfolding futures on particular groups, especially where these are marginalized or minority groups such as people of colour or indigenous groups. Castellani (2020) evidenced this powerfully in relation to coronavirus (Byrne, 2024) and showed why agent-based models are less susceptible to this problem because of their ability to account for the heterogeneity of cases. It is therefore essential to consider who (i.e. which groups) a model may exclude and the effect on which groups the approach to modelling a particular phenomenon may obscure, downplay or diminish.
4) Complexity (but not complicatedness): Modelling-based considerations of the future need to reflect the openness, novelty and emergence that is a fundamental feature of complex reality. However, a clear distinction should be made between complexity and complicatedness. As evidenced in this paper, models that are simple and based on commonplace heuristics can far outperform very complicated models that have thousands of parameters.
5) Relevance over precision: Since our concern is something that does not exist empirically—i.e. the future–and exploring its many possibilities, our priority should be relevance over precision. Our task is to provide broad brush depictions of potential futures, with an emphasis on those that are transformative.
6) Contribution: Where models are presented, this should be done in a way that draws attention to their total value to the field, noting that this goes beyond merely their anticipations and includes their value for marshalling thoughts and evidence, considering alternative or counterfactual outcomes, and explaining and understanding phenomena.

5. Conclusion

This editorial paper has ranged over a broad and varied terrain. Parts of this terrain have undoubtedly been simply pointed at rather than adequately explored. Some of the concepts covered by our exploration, including complexity, nonergodicity, non-stationarity, and undecidability, have been quite technical. We hope we have covered them in an accessible yet accurate way. However, these concepts' individual and collective implications for consideration of the future are easily grasped. Namely, few systems of interest to humans will ever have the stability needed for the forms of modelling considered in this paper to provide a straightforward guide to their futures.

We hope this paper will not be taken to imply that either we, individually, or the journal we edit are averse to modelling or to modelling-based consideration of the future. In many ways, rather than less emphasis on modelling-based considerations of the future in this journal, we would like to see more of it. Indeed, one of the motivations for publishing this paper is the anticipation of an upcoming special issue of Futures that will focus on the use of climate models to construct particular futures.[7] We would also like to see mixed approaches that meld modelling-based consideration of the future with more qualitative methods to achieve a holistic understanding of the multifaceted future. Yet, authors should be cognisant of the six principles we have set out: transparency, reflexivity, inclusivity, complexity (but not complicatedness), relevance (over precision), and contribution. Far from wishing to discourage modelling-based considerations of the future, our intention in setting out these principles is to guide scholars in the futures field towards making contributions that truly advance the field by providing insight that could not be achieved using other methods in isolation from modelling.

[7] https://www.sciencedirect.com/special-issue/324878/constructing-futures-through-climate-modelling

We very much hope to see some excellent papers published in futures in the coming years by authors who have clearly considered and reflected on the important matters we have briefly touched on herein. We also welcome broader discussions and methodological reflections that seek to clarify, challenge or extend the points we have made regarding the use of modelling in the field of futures.

CRediT authorship contribution statement

Zora Kovacic: Writing – review & editing, Writing – original draft. **Richard Sandford:** Writing – review & editing, Writing – original draft. **SJ Beard:** Writing – review & editing, Writing – original draft. **Chris Groves:** Writing – review & editing, Writing – original draft. **James Derbyshire:** Writing – review & editing, Writing – original draft.

Declaration of Competing Interest

All authors of this paper are members of the editorial board of *Futures*. One author is the Editor. The authors declare that no financial interests or personal relationships have influenced the work reported in this paper.

Data availability

No data was used for the research described in the article.

References

Ahl, V., & Allen, T. F. H. (1996). *Hierarchy Theory: A Vision, Vocabulary, and Epistemology*. New York: Columbia University Press.
Aldred, J. (2010). Climate change uncertainty, irreversibility and the precautionary principle. *Cambridge Journal of Economics, 36*, 1051–1072.
Anderson, B. (2010). Preemption, precaution, preparedness: Anticipatory action and future geographies. *Progress in Human Geography, 34*, 777–798.
Anderson, W. (2021). The model crisis, or how to have critical promiscuity in the time of Covid-19. *Social Studies of Science, 51*, 167–188.
Amoore, L. (2013). *The Politics of Possibility: Risk and Security Beyond Probability*. Duke University Press. https://doi.org/10.2307/j.ctv11sms8s
Beard, S., Rowe, T., & Fox, J. (2020). An analysis and evaluation of methods currently used to quantify the likelihood of existential hazards. *Futures, 115*, Article 102469.
Bermúdez, J. L. (2009). *Decision theory and rationality*. Oxford: Oxford University Press.
Bermúdez, J. L. (2020). *Frame it again*. Cambridge: Cambridge University Press.
Bermúdez, J. L. (2022). Rational framing effects: A multidisciplinary case. *Behavioral & Brain Sciences, 45*, Article E220.
Boyd, D., & Crawford, K. (2011). Critical questions for big data: Provocations for a cultural, technological and scholarly phenomenon. *Information, Communication and Society, 15*, 662–679.
Byrne, D. S. (2024). Scenarios–Using the complexity frame of reference to inform the construction of available futures in the possibility space. *Frontiers in Complex System (June 2024*.
Castellani, B. (2020). Modelling the coronavirus: why all public health models are not the same. Available at: 〈https://www.cecan.ac.uk/blog/part-1-modelling-the-coronavirus-whyall-public-health-models-are-not-the-same/〉(Accessed February 9, 2022).
Cox, L. A., Jr. (2020). Answerable and unanswerable questions in risk analysis with open-world novelty. *Risk Analysis, 40*, 2144–2177.
Dalton, C. & Thatcher, J. (2014). What does a critical data studies look like, and why do we care? Seven points for a critical approach to 'Big Data.' Society & Space Open Site. Accessed from 〈https://www.societyandspace.org/articles/what-does-a-critical-data-studies-look-like-and-why-do-we-care〉 2025-01-14.
Derbyshire, J. (2016). The implications, challenges and benefits of a complexity-orientated futures studies. *Futures, 77*, 45–55.
Derbyshire, J. (2020). Answers to questions on uncertainty in geography: Old lessons and new scenario tools. *Environment & Planning A, 52*, 710–727.
Derbyshire, J. (2022). Increasing preparedness for extreme events using plausibility-based scenario planning: Lessons from COVID-19. *Risk Analysis, 42*, 97–104.
Derbyshire, J. (2024). Integrating modelling-based and stakeholder-focused scenario approaches to close the planning gap and accelerate low-carbon transitions. *Ecological Economics, 221*, Article 108208.
Derbyshire, J., & Aven, T. (2025). Out of sight but still in mind: Developing an expectation for surprises by formalising unknowledge in a contemporary risk-assessment framework. *Risk Analysis, 45*, 1199–1206.
Derbyshire, J., Dhami, M., Belton, I., & Önkal, D. (2023). The value of experiments in futures and foresight science as illustrated by the case of scenario planning. *Futures & Foresight Science, 5*, Article e146.
Derbyshire, J., & Morgan, J. (2022). Is seeking certainty in climate sensitivity measures counterproductive in the context of climate emergency? The case for scenario planning. *Technological Forecasting & Social Change, 182*, Article 121811.
Espeland, W., & Yung, V. (2019). Ethical dimensions of quantification. *Social Science Information, 58*, 238–260. https://doi.org/10.1177/0539018419851045
Frigg, R., & Smith, L. A. (2022). An ineffective antidote for hawkmoths. *European Journal for Philosophy of Science, 12*, 1–24.
Funtowicz, S., & Ravetz, J. (1990). Post-normal science: A new science for new times. *Scientific European, 266*, 20–22.
Funtowicz, S. O., & Ravetz, J. R. (1993). Science for the post-normal age. *Futures, 25*, 739–755.
Gigerenzer, G. (2022). *How to stay smart in a smart world*. Penguin Books Limited.
Gilain, A., Le Masson, P., & Weil, B. (2023). Chimera heuristics: Generative rational heuristics for the unknown from design theory. *European Management Review, 20*, 665–678.
Gitelman, L. (2013). *"Raw Data" Is an Oxymoron*. The MIT Press.
Goodhart, C. (1981). Problems of monetary management: The U.K. experience. In A. S. Courakis (Ed.), *Inflation, depression, and economic policy in the west* (pp. 111–146). Totowa: Barnes & Noble Press.
Gorski, P. S. (2013). Beyond the fact/value distinction: Ethical naturalism and the social sciences. *Society, 50*, 543–553.
Harcourt, B. (2006). *Against Prediction: Profiling, Policing, and Punishing in an Actuarial Age*. University of Chicago Press.
Katsikopoulos, K. V., Şimşek, Ö., Buckmann, M., & Gigerenzer, G. (2022). Transparent modelling of influenza incidence: Big data or a single data point from psychological theory. *International Journal of Forecasting, 38*, 613–619.
Kitchin, R., & Lauriault, T. (2014). Towards Critical Data Studies: Charting and Unpacking Data Assemblages and Their Work. The Programmable City Working Paper 2; pre-print version of chapter to be published in. In J. Eckert, A. Shears, & J. Thatcher (Eds.), *Geoweb and Big Data*. University of Nebraska Press. 〈https://ssrn.com/abstract=2474112〉.
Kovacic, Z. (2017). Investigating science for governance through the lenses of complexity. *Futures, 91*, 80–83.
Kovacic, Z., & Biggeri, A. (2023). Post-normal science 30 years on. Editorial introduction: Ongoing conversations about knowledge, science practices, integrity and quality through post-normal lenses. *Futures, 151*, Article 103183.
Kovacic, Z., & Di Felice, L. J. (2019). Complexity, uncertainty and ambiguity: Implications for European Union energy governance. *Energy Research & Social Science, 53*, 159–169.

Kovacic, Z., & Giampietro, M. (2015). Beyond "beyond GDP indicators": The need for reflexivity in science for governance. *Ecological Complexity, 21*, 53–61.
Laudan, L. (1984). *Science and values: The aims of science and their role in scientific debate*. Univ of California Press.
Leamer, E. (1983). Let's take the con out of econometrics. *American Economic Review, 73*, 31–43.
Lekka-Kowalik, A. (2010). Why science cannot be value-free. *Science and Engineering Ethics, 16*, 33–41. https://doi.org/10.1007/s11948-009-9128-3
Le Masson, P., Hatchuel, A., Le Glatin, M., & Weil, B. (2019). Designing decisions in the unknown: A generative model. *European Management Review, 16*, 471–490.
Lucas, R. E. (1972). Expectations and the neutrality of money. *Journal of Economic Theory, 4*, 103–124.
Lucas, R. E. (1976). Econometric policy evaluation: a critique. In K. Brunner, & A. Meltzer (Eds.), *The Phillips Curve and Labor Markets* (pp. 222–236). Amsterdam: North Holland Publishing Company.
Mercure, J.-F., Pollitt, H., Bassi, A. M., Viñuales, J. E., & Edwards, N. R. (2016). Modelling complex systems of heterogenous agents to better design sustainability transitions policy. *Global Environmental Change, 37*, 102–115.
Metcalfe, S., Salles-Filho, S., Duarte, L. T., Bin, A., Azevedo, A. T., & Feitosa, P. H. A. (2021). Shackle's approach towards priority setting and decision-making in science, technology, and innovation. *Futures, 134*, Article 102838.
Mitchell, A., & Chaudhury, A. (2020). Worlding beyond 'the' 'end' of 'the world': White apocalyptic visions and BIPOC futurisms. *International Relations, 34*, 309–332.
Nasir, M. A., & Morgan, J. (2018). The unit root problem: Affinities between ergodicity and stationarity, its practical contradictions for central bank policy, and some consideration of alternatives. *Journal of Post Keynesian Economics, 41*, 339–363.
Parkhurst, J. (2016). *The Politics of Evidence: From evidence-based policy to the good governance of evidence*. Routledge. https://doi.org/10.4324/9781315675008
Patomäki, H. (2019). Reflexivity of Anticipations in Economics and Political Economy" in Handbook of Anticipation. In R. Poli (Ed.), *Theoretical and Applied Aspects of the Use of Future in Decision Making* (pp. 555–580). Cham: Springer.
Pawson, R., Wong, G., & Owen, L. (2011). Known knowns, known unknowns, unknown unknowns: The predicament of evidence-based policy. *American Journal of Evaluation, 32*, 518–546.
Peters, O. (2019). The ergodicity problem in economics. *Nature Physics, 15*, 1216–1221.
Porter, T. M. (2020). *The Rise of Statistical Thinking, 1820–1900*. Princeton University Press. https://doi.org/10.2307/j.ctvxcrz1v
Ramírez, R., & Selin, C. (2014). Plausibility and probability in scenario planning. *Foresight, 16*, 54–74.
Raworth, K. (2022). Doughnut economics: Seven ways to think like a 21st-century economist, Penguin,
Reichmann, W. (2013). Epistemic participation: How to produce knowledge about the economic future. *Social Studies of Science, 43*, 852–877.
Rosen, R. (1985). *Anticipatory Systems*. Oxford: Pergamon Press.
Saltelli, A., Guimaraes Pereira, Â., Van der Sluijs, J. P., & Funtowicz, S. (2013). What do I make of your latinorum? Sensitivity auditing of mathematical modelling. *International Journal of Foresight and Innovation Policy, 9*, 213–234.
Saltelli, A., Bammer, G., Bruno, I., Charters, E., Di Fiore, M., Didier, E., Nelson Espeland, W., Kay, J., Lo Piano, S., Mayo, D., Pielke, R., Jr., Portaluri, T., Porter, T. M., Puy, A., Rafols, I., Ravetz, J. R., Reinert, E., Sarewitz, D., Stark, P. B., Stirling, A., van der Sluijs, J., & Vineis, P. (2020). Five ways to ensure that models serve society: A manifesto. *Nature, 82*.
Saltelli, A., & Giampietro, M. (2017). What is wrong with evidence based policy, and how can it be improved? *Futures, 91*, 62–71.
Saltelli, A. & Di Fiore, M. (eds.) (2023). The Politics of Modelling: Numbers Between Science and Policy. Oxford.
Sherwood, S., Webb, M., Annan, J., Armour, K., Forster, P., Hargreaves, J., Hegerl, G., Klein, S., Marvel, K., Rohling, E., Watanabe, M., Andrews, T., Braconnot, P., Bretherton, C. S., Foster, G. L., Hausfather, Z., von der Heydt, A. S., Knutti, R., Mauritsen, T., Norris, J. R., Proistosescu, C., Rugenstein, M., Schmidt, G. A., Tokarska, K. B., & Zelinka, M. D. (2020). An assessment of Earth's climate sensitivity using multiple lines of evidence. *Reviews of Geophysics, 58*. e2019RG000678.
Suárez, M. (2024). The emergence of the modelling attitude. In Knuuttila Tarja, Carrillo Natalia, & Koskinen Rami (Eds.), *The Routledge Handbook of Philosophy of Scientific Modeling. Routledge Handbooks in Philosophy*. Routledge.
Taleb, N. N. (2008). *The Black Swan*. London: Penguin.
Taleb, N. N. (2020). *Statistical consequences of fat tails: Real world preasymptotics, epistemology, and applications*. STEM academic press.
Thompson, E. (2022). *Escape from model land*. London: Basic Books.
Turing, A. M. (1954). Solvable and unsolvable problems. In A. W. Heaslett (Ed.), *Science News* (pp. 7–23). Harmondsworth, Middlesex, England: Penguin Books.
Waltner-Toews, D., Biggeri, A., De Marchi, B., Funtowicz, S., Giampietro, M., O'Connor, M., & van der Sluijs, J. P. (2020). Post-normal pandemics: Why CoViD-19 requires a new approach to science. *Recenti Progressi in Medicina, 111*, 202–204.
Wynne, B. (1992). Uncertainty and environmental learning—Reconceiving science and policy in the preventive paradigm. *Global Environmental Change-Human and Policy Dimensions, 2*(2), 111–127.
Wynne, B. (2010). Strange weather, again. *Theory, Culture & Society, 27*, 289–305. https://doi.org/10.1177/0263276410361499
Zellmer, T. F. H., Allen, K., & Kesseboehmer, K. (2006). The nature of ecological complexity: A protocol for building the narrative. *Ecological Complexity, 3*, 171–182.