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UNDERSTANDING AND COMMUNICATING UNCERTAINTY IN DATA-RICH ENVIRONMENTS: TOWARDS A TRANSDISCIPLINARY APPROACH

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Abstract

Agricultural and environmental decision-making are increasingly driven by information derived from data-rich digital sources. Biophysical models can help to interpret the growing amount of data and to manage associated uncertainties, but they cannot address all and might even introduce new uncertainties. Discourses concerning modelling therefore feature a range of uncertainties that promote a plethora of meanings, particularly once models are used to support decision or policy-making. Communication in these contexts can remain vague unless these diverse meanings are understood. Drawing on interdisciplinary agricultural research, we propose a framework that distinguishes between the *direct* uncertainty associated with a specific biophysical model itself, *indirect* uncertainties that concern underlying knowledge or users' trust, and *contextual* uncertainties that emerge from the wider setting within which models are embedded. We also draw attention to the processes of data generation and model building themselves. Framing uncertainty in this way is useful for several reasons. First, it helps to identify different types of modelling uncertainties. This, secondly, allows interdisciplinary research teams to delineate work areas and establish productive collaboration. Third, the framework might help facilitate meaningful developer-user dialogue around models' strengths and limitations, which is crucial for expectation management and model improvement. Fourth, this understanding can support decision-making in contexts where a lot of information and uncertainty emerge from data-rich, digital sources.

Introduction

Decision making in farming operations and the environmental regulation of agricultural systems are increasingly dependent on information derived from digital data that is generated by smart sensors (animal, ground, aircraft or satellite mounted), Internet-of-Things devices or cloud computing. Digitalisation provides a growing volume of increasingly real-time big data to smart farming operations, consumers and others along the supply chain (Smith 2020; Wolfert et al. 2017). Ecological and biophysical agricultural models—colloquially known as crop or process simulation models—can help to interpret the growing amount of data, as well as support agricultural decision-making and environmental regulation (Meenken et al., this volume; Schmolke et al. 2010; Schuhwirth et al. 2019). While models may reduce some of the uncertainties associated with complex decision-making, they cannot address others and might even introduce new uncertainties. Modellers and users make frequent reference to uncertainties, but it is often unclear which specific aspects of a model are discussed or whether they even concern the model itself. As a result, discourses around modelling uncertainty can feature a wide range of different uncertainties and promote a plethora of meanings (e.g. PCE 2018). Communication within decision-making processes can therefore remain ambiguous and potentially ineffective unless these diverse meanings are understood and appreciated by all parties. Drawing on interdisciplinary research across various agricultural projects around improved sensor measurements and crop modelling, we propose a conceptual framework to understand modelling uncertainties more holistically. This is a critical first step towards facilitating meaningful communication around models' merits and limitations within decision-making processes.

While a large body of scholarship exists around multi-, inter- and transdisciplinary research, those terms are often used interchangeably. Their practical application can thus lack clear principles, methods and overarching strategy. Following Lawrence (2010), we regard interdisciplinarity as the collaboration and cooperation of scientists from different disciplines who contribute their specific competence to address common research questions and achieve shared results. Establishing such a research environment is the foundation for transdisciplinary approaches that go beyond cooperation. Such approaches generally accept the non-linearity and open-endedness of scientific research and knowledge production. This, in turn, prompts reflexivity, inter-subjectivity, and a shared appreciation for the complex entanglements of social, organisational, and biophysical contexts (Barry & Born 2013; Lawrence 2010).

We begin by briefly outlining a social scientific perspective that stresses a relational understanding of modelling uncertainties. This outline is intended to be complementary to those presented across the *Uncertainty in Measurement and Modelling* session of this conference, which features various disciplinary approaches from the social, applied and natural sciences. Taken together, these papers demonstrate the range of different uncertainties—and unknowns generally—that should be considered in relation to digital data-rich environments and biophysical agricultural models. We then introduce a conceptual working framework to capture this variety and describe its key tenets, which is based on a distinction between direct, indirect and contextual uncertainties. The concluding remarks include critical reflections on the practical advantages of our conceptual framing for establishing an interdisciplinary research programme and how these insights might be applicable more broadly to support decision-making in contexts where a lot of information and uncertainty emerge from data-rich digital sources.

Uncertainty: A relational view from the social sciences

Nearly all academic disciplines have something to say about uncertainty, making it a ubiquitous and elusive notion that can evoke diverse meanings and responses (Smithson, 2008). An initial understanding of uncertainty as lacking complete knowledge seems plausible but does not allow differentiating it from associated terms, such as risk or ignorance, and to unpack some of its inherent complexities. This semantic ambiguity—itself *linguistic* uncertainty (Carey & Burgman 2008)—can be problematic, particularly when crucial agricultural management or policy decisions are based on uncertain information. It is therefore important to clarify what is meant by uncertainty and how it pertains to biophysical modelling.

To begin with, it is insightful to reflect on what constitutes knowing and not-knowing generally. Knowledge is a sociocultural phenomenon that involves sociality and intersubjectivity. This means that it depends on knowing individuals who are suspended in social relationships and culturally shared webs of meaning (Geertz 1973; Knoblauch 2005). Knowledge is a form of meaning that can be shared with others within those webs. Knowing is thus not the mere possession of externalisable information but a form of cognitive doing by socially situated agents—knowledge must be known. For an individual, knowledge forms part of her 'capacity to act' upon and engage with the biophysical and social world (Barth 2002; Stehr 2001).

This perspective equally applies to not-knowing, which shows that it is not merely an absence of sufficient information. Instead, social scholars have stressed the positivity of not-knowing and demonstrated that it equally "provides the grounds for action, thought and the production of social relations" (Kirsch & Dilley 2015: 21). Between the extremes of 'unknown unknowns' and widely accepted knowledge, stretches a wide middle ground spectrum that includes known or suspected unknowns, not-yet-knowns and desired unknowns.[1] Not-knowing is thus not necessarily a negative or undesirable absence of information (Smithson 2008; Wilson et al. 2005). For example, partial knowledge is usually a key impetus for scientific research, while uncertainty can fulfil various positive social functions from allowing for creativity to generating excitement over the outcome of sporting events.

Seen through a relational lens, it is therefore necessary to consider unknowns together with what is (claimed to be) known. The resulting epistemic complexities require clear terminologies of specific unknowns, as, for instance, shown in the taxonomy presented in Figure 1 (see also Wheeler et al., this volume):

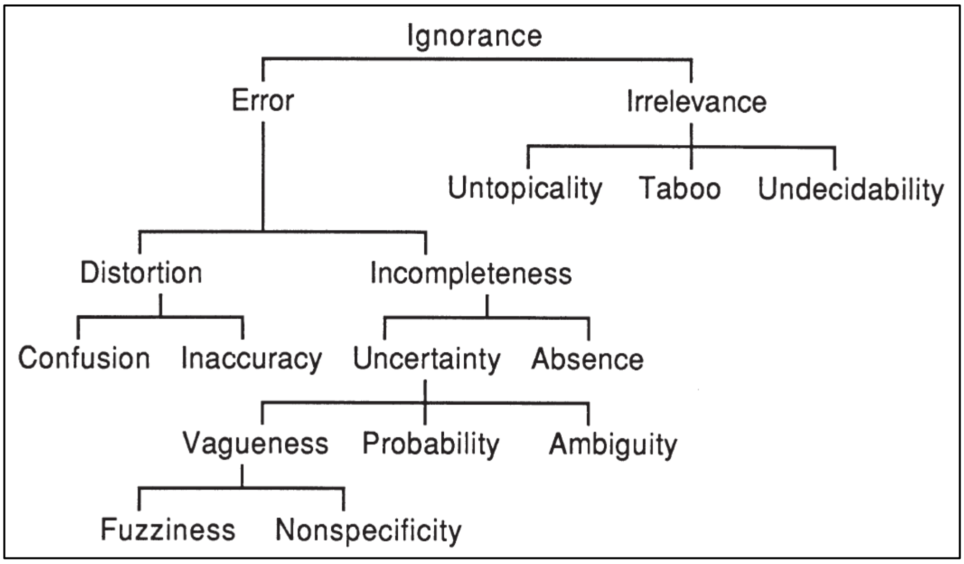

Figure 1 Taxonomy of Ignorance (source: Smithson 1989: 9)

Notwithstanding that Smithson's taxonomy and its applicability to agricultural or environmental decision-making require critical evaluation—which is beyond the intended scope—, it highlights, firstly, that uncertainty is but one manifestation of unknowns. Secondly, his taxonomy indicates that uncertainty itself can be internally differentiated.

One example is the relationship between the often-synonymised notions of uncertainty and risk. The economist Frank Knight (1921: 19–20, original emphasis) emphasised that uncertainty is non-quantifiable and "radically distinct" from risk, which is "a quantity susceptible of

[1] Wehling (2006: 116–149) examines three interconnected dimensions for characterising unknowns: the level of knowledge about unknowns; the intentionality of not-knowing; and the temporal stability of unknowns (see also Espig 2018: 33–39).

measurement … a *measurable* uncertainty". Brian Wynne (1992) takes this distinction further and differentiates between four unknowns in policy contexts:

- **risk**: a system's behaviour and the odds of different outcomes are well-known and quantifiable
- **uncertainty**: only general system parameters but not their probability distributions are known
- **ignorance**: 'we don't know what we don't know'; policy decisions might be made without any knowledge about, e.g., unintended consequences
- **indeterminacy**: the contingencies associated with human behaviour; policy contexts are often characterised by a "real open-endedness in the sense that outcomes depend on how immediate actors will behave" (ibid.: 117).

We would argue that some uncertainties are quantifiable and that probability distributions around uncertain aspects can be known. Risks are therefore not the only type of quantifiable unknowns, nor are all risks quantifiable. Nonetheless, both Knight's and Wynne's distinctions point towards crucial questions around modelling uncertainty. Perhaps most importantly, it should be stressed that knowledge of unknowns, including uncertainty and risk, is **conditional** and **context-specific**; almost certain outcomes and risks in one setting may be more uncertain in another due to altered parameters, and may depend upon assumptions about human or animal behaviour.

Understood through this relational lens, "[u]ncertainty refers to the situation in which there is not a unique and complete understanding of the system to be managed" (Brugnach et al. 2008: 4). By highlighting uncertainty's equivocality, Brugnach et al. argue that in addition to *ontological* uncertainty (e.g. unpredictability or randomness) and *epistemic* uncertainty (e.g. lack of settled knowledge), a third kind of uncertainty exists, namely *ambiguity* that emerges from the multiple knowledge frames through which uncertainty can gain meaning.[2] Uncertainties are therefore socially co-constructed in tandem with biophysical aspects. Combining symbolic and material insights in this way shows that "uncertainty cannot be understood in isolation but only in the context of the socio-technical-environmental system in which it is identified" (Brugnach et al. 2008: 11–12).

These insights inform discussions around uncertainties associated with measurements and biophysical agricultural models (see Meenken et al. and Sharifi et al., this volume). Adding sociocultural insights to these perspectives becomes particularly important once data generation and modelling are considered in the context of decision and policy-making. It is crucial to understand modelling uncertainties holistically in order to prevent challenges regarding models' legitimacy in these processes and any legal implications, as has been shown in the context of New Zealand's environmental regulation (Guillaume et al. 2012; Özkundakci et al. 2018; PCE 2018; Schmolke et al. 2010). It is subsequently also necessary to frame and communicate those understandings effectively (Doyle et al. 2019; Guillaume et al. 2018; van der Bles et al. 2019).

To summarise, we propound that a relational perspective is essential for grasping the sociocultural dimensions of uncertainty generally and as those pertain to measurement and modelling in particular. This means, firstly, that uncertainty is but one manifestation of the interplay between knowing and not-knowing. As such, it should be clearly distinguished from

[2] On the notions of ontological, aleatory and epistemic uncertainty see also the other papers in this session.

closely related notions and differentiated internally. Second, uncertainty is also relational in that it can be subject to multiple epistemic frames, which might lead to ambiguity and different underlying understandings of uncertainty. Third, we consider uncertainties as relational in that they depend on the contextual relationships of socio-technical-environmental systems, which highlights that *social and biophysical contexts matter*.

A conceptual framework for uncertainties in and around modelling

It is, prima facie, difficult to determine if and how the diverse facets of measurement and modelling uncertainty, which are described across the papers in this panel, might be relatable within a systematic approach. Helpful typology matrices and classification systems have been proposed (e.g. Walker et al. 2003; for a systematic review see Doyle et al. 2019), but these are either less applicable in the initial stages of interdisciplinary research due to their specificity, which requires existing shared epistemic frames, or they do not fully account for the contextual relationships of socio-technical-environmental systems we described. To address these challenges, we developed a simple conceptual framework of different meta-categories of uncertainties *in and around* modelling that is intended as an initial starting point for interdisciplinary projects and a holistic understanding of modelling uncertainties.

Our conceptual distinctions build on van der Bles et al. (2019) who suggest two different levels of uncertainty. They distinguish between uncertainty directly about epistemic ‘objects’ and more indirect ‘meta-uncertainty’ about the underlying evidence for their assessment (ibid.: 7):

> *Direct* uncertainty about the fact, number or scientific hypothesis. This can be communicated either in absolute quantitative terms, say a probability distribution or confidence interval, or expressed relative to alternatives, such as likelihood ratios, or given an approximate quantitative form, verbal summary and so on.
>
> *Indirect* uncertainty in terms of the quality of the underlying knowledge that forms a basis for any claims about the fact, number or hypothesis. This will generally be communicated as a list of caveats about the underlying sources of evidence, possibly amalgamated into a qualitative or ordered categorical scale.

Van der Bles et al. (2019: 8) provide an analogy to illustrate the direct-indirect distinction, drawing on the archetypical components of a legal case that seeks to determine a suspect’s guilt. Imagine a court room where a forensic expert provides evidence in a criminal case. Direct uncertainty would refer to the given evidence regarding the suspect’s guilt, while indirect uncertainty concerns the credibility of the forensic expert’s testimony.

Van der Bles et al. primarily examine the communication of direct uncertainty. Understanding those uncertainties in the first place does, however, require insights into how and why a specific model was produced as support for a decision or policy-making process (Guillaume et al. 2012, 2016; Schuwirth et al. 2019). The direct uncertainties that are introduced ‘indirectly’ during data generation, model selection and model building therefore should be critically evaluated. We further believe that the direct-indirect distinction can be expanded.

To do so, we integrate social insights into an understanding of indirect uncertainty. This entails considering actors and their relationships, which implies not only a concern with underlying knowledge per se but also those claiming to hold and negotiating that knowledge. Within the context of agricultural or environmental decision-making, for example, fully assessing specific facts or numbers and the quality of underlying (scientific) knowledge upon which these are based might only be feasible for expert practitioners or researchers. It is therefore reasonable for non-experts to assess the direct and indirect modelling uncertainties by assessing the qualifications, motives or trustworthiness of those making claims about knowledge or uncertainty—an assessment 'by proxy'. This is an additional facet of indirect uncertainty.

Second, we build on the outlined perspective that uncertainties are at least partially conditional, context-specific and potentially subject to multiple epistemic frames. We thus propose a complimentary third level of uncertainty:

> *Contextual* uncertainty about the wider setting of the production and application of facts, numbers or scientific hypotheses. It can be expressed qualitatively in a similar vein to indirect uncertainty but relates more to the background conditions within which facts, number or scientific hypotheses are produced and become embedded in once they are utilised for decision or policy-making.

Comparable to Benessia and De Marchi's (2017) notion of 'situational uncertainty', we employ the concept of contextual uncertainty to stress that in most applied settings multidimensional uncertainties exist that cannot be reduced to scientific factors but also spring from legal, moral, societal, institutional and proprietary aspects associated with decision-making. Using the legal analogy, an observer may trust a forensic expert's ability and presented evidence yet still be uncertain about how judges will incorporate this testimony or whether a court is under political pressure to deliver a certain verdict. This analogy is readily applicable to agricultural and environmental decision-making if one considers, for example, regulatory debates around simulated off-farm nitrate leaching, the capabilities of employed models and modellers, as well as stakeholders' potentially conflicting political, commercial or individual interests.

This view problematises a reduction of complex sociocultural phenomena solely into scientific conceptions (Espig & de Rijke 2016: 84). However, scientific insights are of course indispensable components of informed decision-making. We therefore examine contextual factors *in tandem with* direct and indirect uncertainties, which avoids a misleading bifurcation of modelling uncertainty into scientific and non-scientific aspects. This includes an appreciation for the fact that various scientific and non-scientific factors are usually interlinked in actual settings and should thus be analysed holistically. To highlight the interconnectedness between different quantitative and qualitative modelling uncertainties, we proposed a triangular visual representation that positions direct uncertainty in the top third of the triangle, including the processes of data generation, model selection and model building. Indirect and contextual uncertainty form the middle and bottom third, respectively. From all three levels, information and uncertainties cascade through to the bottom of the triangle where eventually decisions are made within a given contexts (see Figure 2).

While cascading representations of widening uncertainties are not new (e.g. Maslin 2013; Wilby & Dessai 2010), we found a triangular depiction to be effective in communicating within the interdisciplinary team and with external partners. The same outcome may be achieved by visualising different levels of modelling uncertainty as concentric circles, with direct uncertainty at the centre and indirect and contextual uncertainty wrapped around it.

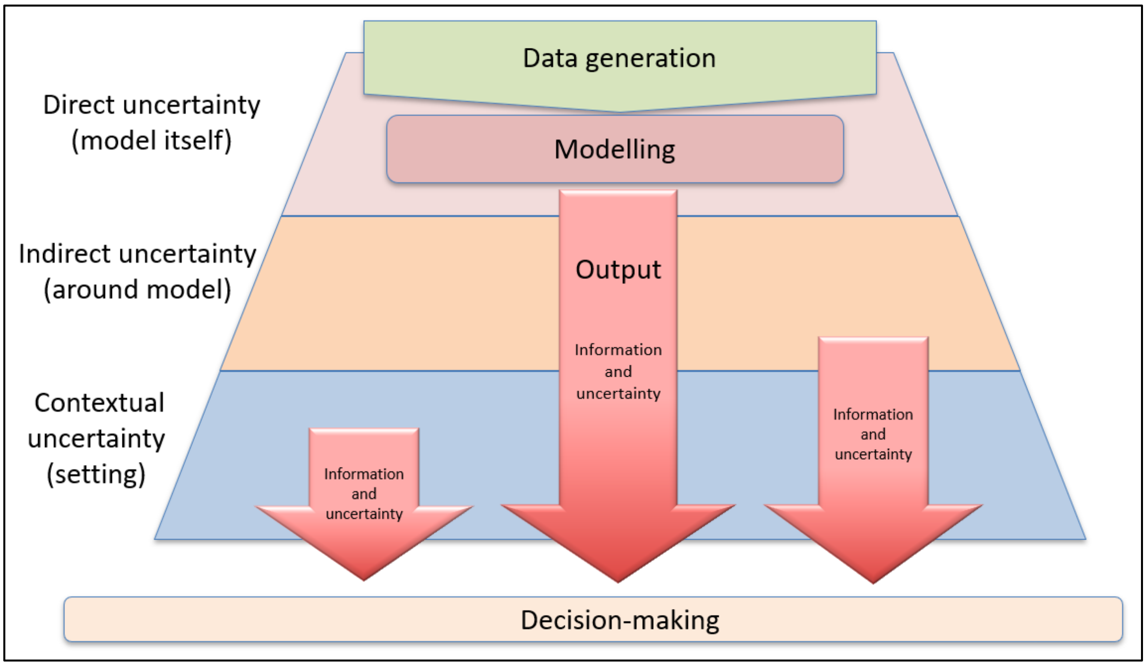

Figure 2 A conceptual framework that describes the interconnection of modelling uncertainties (source: authors)

Three caveats are worth mentioning. First, going visually wider top-to-bottom does not necessarily imply quantitative or qualitative increases of uncertainty but a widening of aspects to consider. We thus caution against the notion that modelling outputs become 'more' uncertain because of their incorporation into decision and policy-making contexts. It is therefore important to equally consider direct, indirect and contextual uncertainties. Second, most modelling practices and the use of modelled information do not progress linearly through separate stages, but usually involve iterative steps and, ideally, feedback loops between data generation, modelling, and application. A cascading representation does therefore not imply a unidirectional diffusion of modelled information, which might be a slippery slope leading to simplistic public deficit of scientific information models. Third, highlighting the meta-level locations and sources of potential modelling uncertainties is only a first step. One needs to subsequently unpack specific types, levels and characteristics of different uncertainties (e.g. Walker et al. 2003), as well as examine more closely the interconnected processes from data generation to the application of modelled information in decision-making

Critical reflections and concluding remarks

The primary purpose of co-developing this framework was to establish the foundations for interdisciplinary research, initially within our AgResearch team but with the potential to incorporate external partners and stakeholders in order to move towards transdisciplinary research. Interdisciplinary approaches are now a well-established response to the realisation of the ecological, social and technical complexities of problem-oriented environmental research. Another factors that prompts increasing calls for interdisciplinarity is a changing and continuously evolving relationship between science and wider society, with issues of accountability of growing importance (see Barry & Born 2013). Like many research organisations, we therefore strive for responsible research and innovation that corresponds to concerns from agricultural stakeholders and the wider New Zealand public (Eastwood et al.

2019; Owen et al. 2013). However, actually facilitating auspicious interdisciplinary research can be challenging.

Gabriele Bammer's work on Integration and Implementation Sciences (I2S) is insightful (Bammer 2013). She outlines crucial core principles that are a prerequisite for interdisciplinary research and describes a number of specific methods to guide such projects. Apart from dialogue and common metric-based methods, Bammer highlights model-based methods as one way to establish commonly shared goals and objects of study. In this sense, a model can be "a device which provides a focal point for discussion and action between people representing different disciplinary perspectives and different types of practical experience relevant to the issue under consideration. It provides a way of organizing different pieces of information" (Bammer 2008: 34). It is the notion of synthesising multiple epistemic frames and bodies of expertise that concerned our research.

A lack of shared uncertainty definitions and categories initially constituted a major challenge for our team. Our conceptual framework helped to clarify some of this confusion, ordered the mosaic of different perspectives, and, thereby, formed the basis for more meaningful dialogue and system-based thinking across team members. In this sense, the meta-categories we developed are one example of a model-based method for synthesising multiple epistemic frames into an interdisciplinary approach that has more explanatory potential than discipline-specific insights by themselves. The framework functions as a 'boundary object' that is flexible enough to equally incorporate individual team member's disciplinary expertise, while still being robust enough to create a common understanding (Star & Griesemer 1989). Co-developed conceptual frameworks, visual models or discursive devices are thus indispensable for initiating effective interdisciplinary research and we propose that our conceptualisations around measurement and modelling uncertainties can be utilised in this way.

To summarise and reflect on key findings, we argued that, firstly, our framework helps to identify different meta-categories of modelling uncertainties. This, secondly, allows interdisciplinary research teams to delineate work areas and establish productive collaboration. Third, while we had initial correspondence with external research partners, a next step will be to determine whether our framework is also helpful in establishing auspicious inter-institutional collaboration and transdisciplinary research. We further aim to test if it can serve as a foundation for more effective communication of modelling uncertainties among agricultural stakeholders, modellers and policymakers, which is crucial for expectation management and model improvement. Lastly, recent research has demonstrated that the framing and communication of uncertainty is crucial for robust individual and collective decision-making (Doyle et al. 2019; Guillaume et al. 2018). Our framework might serve as a first point of reference to realise this goal and, in turn, support decision-making in contexts where a lot of information and uncertainty emerge from data-rich, digital sources.

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