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UNCERTAINTY – WHAT IS IT?

Wheeler, D.M., Meenken, E.D., Espig, M., Sharifi, M., Shah, M. and Finlay-Smits, S.C.

AgResearch, Ruakura Research Centre, Private Bag 3123, Hamilton
AgResearch, Lincoln Research Centre, Christchurch
Email: David.wheeler@agresearch.co.nz

Abstract
All knowledge on which decisions are made is shrouded with uncertainty of different types and degrees. Addressing uncertainties in data-rich environments is complex and no discipline can do it all, hence interdisciplinary approaches are crucial. Digitalisation in agriculture provides more and increasingly real-time data from smart on-animal and on-farm sensors and IoT devices, but there are uncertainties associated with this data. Simulation models can turn this data into actionable knowledge for decision-making but are also accompanied by uncertainties. These might concern how the data is collected, the modelling itself, and the inherent assumptions. The model or its outputs are used in a wider context, where uncertainty related to ambiguity, probability or vagueness becomes important. Uncertainty is thus a fuzzy term that describes a plethora of quantitative and qualitative aspects of limited knowledge. This paper discusses uncertainty at a broad level as an introduction to following papers which jointly aim to increase discussion about uncertainty and its role in decision making.

What is uncertainty
Generalised definitions of uncertainty mention words like ‘not able to rely on’, ‘not knowing’, and ‘having doubt’. Wikipedia defines uncertainty as a state of limited knowledge where it is impossible to exactly describe the existing state, a future outcome, or more than one possible outcome. It further adds ‘Uncertainty refers to epistemic situations involving imperfect or unknown information. It applies to predictions of future events, to physical measurements that are already made, or to the unknown. Uncertainty arises in partially observable and/or stochastic environments, as well as due to ignorance, indolence or both. It arises in any number of fields, including insurance, philosophy, physic, statistics, economics, finance, psychology, sociology, engineering, metrology, meteorology, ecology, and information science. A social oriented definition proposed by Walker et al. (2003) is ‘Any departure from the unachievable ideal of complete determinism’. In models, definitions of uncertainty centre around how well the data or the model is an emulation of the real system. Cunha (2017) notes that model uncertainty is due to lack of knowledge about the phenomenon of interest and, usually, is the largest source of inaccuracy in computational model response. Cuzzolin (2016) notes that ‘Uncertainty can be understood as lack of information about an issue of interest for a certain agent (e.g., a human decision maker or a machine), a condition of limited knowledge in which it is impossible to exactly describe the state of the world or its future trajectories’.

A common theme in the definitions is that uncertainty is linked to lack of information, or unknowns. Smithson (1989), in one example of a typology of the source of ignorances (a social science term for unknowns) identified uncertainty as one of the ignorances, and divided uncertainty into 3 categories (Figure 1); vagueness, probability and ambiguity, where vagueness relates to a range of possible values on a continuum; probability refers to the laws of chance; and ambiguity refers to a finite number of distinct possibilities. A possible impact of these categories is referred to later.

In this sense, ignorance and uncertainty are neither negative nor positive; rather, they are neutral terms describing a state of being. Bammer (2013) noted that vagueness and ambiguity are essential for research to proceed, especially in the early stages. Uncertainty in social life and decision-making adds to the ‘spice of life’. Army researchers have discovered that being initially uncertain when faced with making critical mission-related decisions may lead to better overall results in the end (ScienceDaily, 2018). In these cases, uncertainty is a positive attribute.

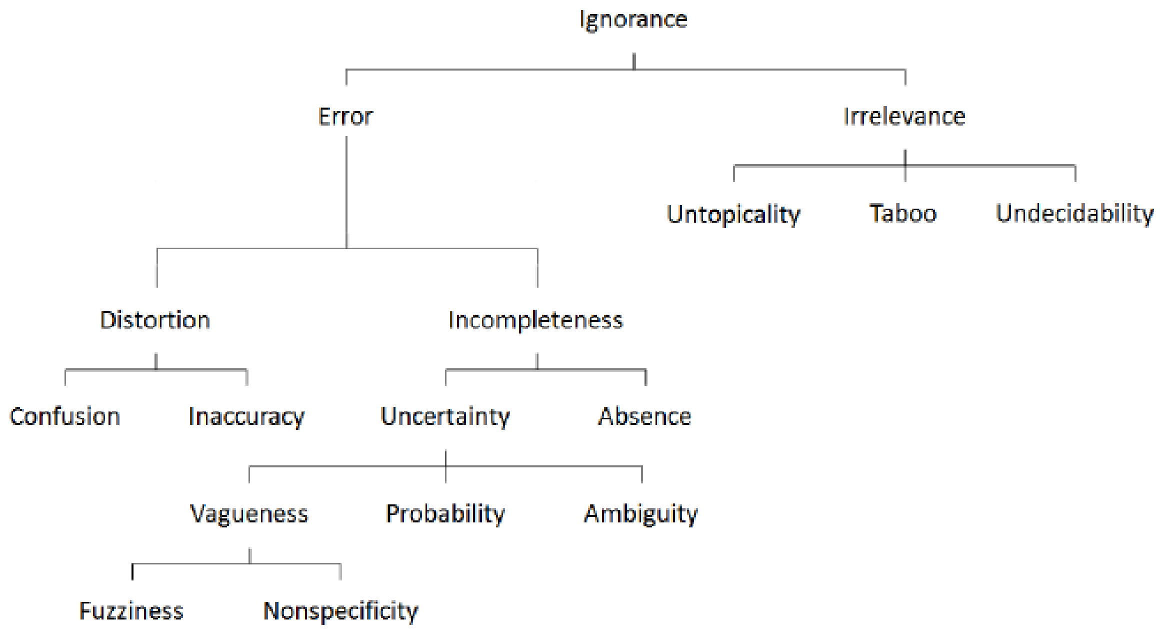

Figure 1. Typology of ignorance (from Smithson, 1989)

Uncertainty is frequently confused with other measures. Uncertainty is not error, accuracy, precision, verification or validation (Trucano et al. (2005), Cunha (2017), Sharifi et al. (2020)). Shepherd et al. (2013) discussed differences in error, precision, and uncertainty in relation to Overseer.

Why consider uncertainty

Uncertainty is an inherent part of knowledge (van der Bles et al., 2019). Cuzzolin (2016) noted that ‘Uncertainty is of paramount importance in artificial intelligence, applied science, and many other areas of human endeavour.’ Every decision, whether made by human or machine, has elements of uncertainty.

Epistemic uncertainty represents a more general and resolvable lack of knowledge that may be able to be reduced through additional data, new techniques, modifying the model, etc. Publications on epistemic uncertainty have risen rapidly over the last five years. In Scopus, last year there were 3250 documents related to epistemic uncertainty. Excluding 2019, 85% of the papers were published in the last 10 years, and 50% in the last 5 years. Of these papers, 50% are from the engineering and metrology subject area; 300 (9%) from environmental sciences and only 64 papers (2%) pertain to the agricultural and biological sciences. The common theme in these publications is that there are increasingly methods being applied to identify multiple sources of uncertainty, and where in the system identifying and addressing these uncertainties can result in ‘better’ decisions (outcomes). However, this work is being predominately undertaken in industries other than agriculture.

Atlas (2019) noted that in general, people have a strong preference for certainty, tending to overweigh options that are certain, and to be risk-averse for gains but are loss-averse, and therefore tend to give losses more weight than gains. New Scientist in an article entitled 'Worried about the future? The science behind coping with uncertainty' reported on the effects of uncertainty on health. This article noted that not coping well with uncertainty can take a toll on our physical and mental health, and our ability to tolerate periods living in limbo has decreased over the past few decades, in part attributed to digital technology (i.e., the smart phone). The authors noted that people's way of perceiving uncertainty and the capacity for coping with uncertainty varies between individuals, and this affects the type of treatments that may be selected, that is, individuals' perception of uncertainty was influencing the decisions they made.

Bammer (2013) noted that based on Smithson's typology, ambiguity is prominent in law where nuances of interpretation can be critical.; vagueness and probability is resolved through statistics; and distortion, another source of ignorance, through intelligence. Hence a legal solution may not resolve probability uncertainty, and probability uncertainty cannot be legislated away. The discipline of statistics primarily operates in the area of incompleteness, across probability and some kinds of vagueness, but doesn't deal with absence or irrelevance (issues that are deliberately or unconsciously overlooked) (Bammer, 2013). The implication is that understanding or reducing uncertainty at a whole system level from the acquisition of information to the outcome of applying that information, particularly where multiple institutions may be involved, requires an interdisciplinary approach where the types of uncertainty are identified using appropriate methods, the uncertainties that matter are identified, and appropriately incorporated into decision making system.

Uncertainty can also be key components in other concepts. For example, in a webinar Spiegelhalter (Winton Centre, Cambridge University, 2019), based on the work of O'Neil, indicated that a focus should be on demonstrating trustworthiness rather than trust, and this requires science to inform not persuade, to be intellectual, open and confident about uncertainty, and to respect the audience. As an aside, trustworthiness is an increasingly key component of value chains.

Understanding uncertainty is accepting that it is an inherent part of knowledge, that people differ in how they deal with uncertainty, that there are different methods for identifying and quantifying uncertainty, and that different uncertainties have different impacts (Bammer (2013), Gluckman (2016), AtLas (2019), Kale et al. (2019), Sniazhko (2019)).

Risk and uncertainty

There is a wide range wide of literature on definitions of risk and the relationship with uncertainty. Risks are derived from uncertainty, that is all risks are uncertainty, but not all uncertainties are risk (Hillson, unknown; Toma et a., 2012). Gooen (2016) noted that risk is known unknowns whereas uncertainty is unknown unknowns. Hillson (unknown) defined risk as "uncertainty that matters' or in more detail risk as "an uncertainty that if it occurs could affect one or more objectives. This recognises the fact that there are other uncertainties that are irrelevant in terms of objectives, and these should be excluded from the risk process'. In economics, Knightian uncertainty is a lack of any quantifiable knowledge about some possible occurrence, as opposed to the presence of quantifiable risk (e.g., that in statistical noise or a parameter's confidence interval). The concept acknowledges some fundamental degree of ignorance, a limit to knowledge, and an essential unpredictability of future events (Wikipedia).

Uncertainty around the future is often expressed through the notion of risk, particularly if the odds are known and calculable. For instance, Toma et al. (2012) noted that

> *'Risk refers to situations in which probabilities targets can be identified for possible results. In other words it can be quantified.' and '…when the information necessary for understanding and anticipating developments, or changes that may occur in a particular context are either insufficient or unavailable, the situation is defined as uncertain.'*

This paper doesn't deal with risk but acknowledges that definitions and concepts of uncertainty and risk vary between disciplines.

Living with uncertainty

Uncertainty can have an impact in multiple levels of the decision-making process. Fischhoff and Davis (2013) notes that 'All science has uncertainty. Unless that uncertainty is communicated effectively, decision makers may put too much or too little faith in it'. Reckhow (1994) cautioned that 'uncertainty in environmental decision making should not be thought of as a problem that is best ignored'. Martin and Johnston (2019) noted that decision makers need to consider imperfect information on the cost and effectiveness of treatments to mitigate environmental impact. In other words, uncertainty should be part of any study involving links to decision making.

Van der Bles et al. (2019) noted that 'in an era of contested expertise, many shy away from openly communicating their uncertainty about what they know, fearful of their audience's reaction.' They proposed a range of methods that have decreasing precision in the way uncertainty was expressed, ranging from a full explicit probability distribution, pre-defined categorisation of uncertainty, a qualifying verbal statement, and informally mentioning the existence of uncertainty, to explicit denial that uncertainty exists. In a webinar, Spiegelhalter noted that when communicating uncertainty, it was important to know the audience, know what you want to achieve, test different formats, and choose one that fulfils your objectives. In other words, communication of uncertainty is dependent on the objective of the uncertainty analysis. Van der Bles et al. (2019) describe in more detail the outcomes of not communicating uncertainty well.

There is a vast amount of literature on methods for assessing uncertainty which is outside the scope of this paper. For example, statistical techniques for models can be used (see Meenken et al., 2020) to identify uncertainty in input parameters, model structure, or internal parameters, and between epistemic uncertainty and aleatory uncertainty (that due to random error). In modelling, it is common to quantify the uncertainty in the prediction due to uncertain model inputs, but methods for quantifying uncertainty due to inadequacies in model structure are less well developed (Strong et al., 2012). An underlying message from this literature is that the methods used to assess uncertainty depend on the purpose of the analysis and is consistent with Spiegelhalter webinar.

There are also a range of methods for incorporating uncertainty into decision making. For instance, the precautionary principle can be applied (Gullett, 1997). Principle 15 of the Rio Declaration on Environment and Development (United nations, 1992) states that 'the precautionary approach shall be widely applied by States according to their capabilities. Where there are threats of serious or irreversible damage, lack of full scientific certainty shall not be used as a reason for postponing cost-effective measures to prevent environmental degradation'. Adaptive management can also be used (ATLAS, 2019).

Understanding uncertainty provides a better understanding of the future and how to control or predict it, and the range of precautionary behaviours required when making decisions to increase the likelihood that the desired outcome is achieved. The Institute of Medicine (2013) summed these points as:

> *The appropriate uncertainty analysis for a decision—and how to consider uncertainty in a decision—will depend on the types, source, and magnitude of the uncertainty as well as on the context of the decision (for example, the severity of the adverse effects and the time frame within which a decision is needed).*

Uncertainty also applies to digital technologies. There is uncertainty associated with data collection (see Sharifi et al., 2020). Frameworks for assessing uncertainty have been proposed for deep learning ensembles (Kachman et al. 2018; Lakshminarayanan et al., 2017; Sacha et al., 2016). This indicates that digital technologies and more data will not remove uncertainty; rather it may change the type uncertainties and provide additional techniques to identify (Solomatine and Shrestha, 2009) and visualise uncertainty (Sacha et al., 2016).

Uncertainty in digital agriculture

As part of the program of work entitled 'New Zealand Bioeconomy in the Digital Age,' an interdisciplinary team in a small project investigated decision making in an agricultural system, particularly as digitalisation increased, through the lens of uncertainty. The group included a modeller, biological scientist, statistician, engineer, meteorologist, data scientist and two social scientists, and it became glaringly apparent that even in this small group, we were talking about different concepts of uncertainty. This is not unusual; the need for a shared language and a methodological framework in interdisciplinary/transdisciplinary research has been reported previously (Payne et al., 2015). Sniazhko (2019) noted that in existing research there was 'inconsistency in the conceptualization and measurement of uncertainty, lack of diversity regarding the dimensions of uncertainty included in single studies and downplaying the role of individual decision-makers'.

This paper indicates that uncertainty is an inherent part of knowledge, that people differ in how they deal with uncertainty, and that different uncertainties have different methods of assessment and impact on desired outcomes. It is contended that when looking at decision making involving complex systems the following should be considered:

- Identification of the type and level or size of uncertainty at different places in a system.
- Identification of the uncertainties that matter – those that may materially impact on the desired outcomes for a given context (and possibly individual).
- Identification of the means to communicate that uncertainty given that users perceive uncertainty differently.
- Identification of mechanisms to account for uncertainty, for instance, converting uncertainty to risk and implementing a risk management plan, improving modelling techniques or data collection, or incorporating uncertainty in the decision-making process for, example, using adaptive management.

This assessment should be across the system, for instance, when a model is used to inform practice in a regulatory environment, the focus should be on how the uncertainties in the data, model, practice and regulation interact. A whole system approach to reducing uncertainty requires a multidisciplinary approach. However, 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). Hence communicating uncertainty across multiple disciplines is critically important.

At this conference there are a series of five papers, including this one as an introduction, and three that focus on uncertainty in sensors and collected data (Sharifi et al., 2020), uncertainty in models (Meenken et al., 2020), and uncertainty when disparate data sets are used (Shah et al., 2020). The fifth paper (Espig et al., 2020) presents a framework that includes these sources of uncertainty along with the concept of 'contextual' uncertainty that is sufficiently robust to enable meaningful dialogue about uncertainty and its role in decision making. Uncertainty is defined in many ways in different academic areas. It is confusing as the same words are used with different meanings and or the same meanings are given to different words. The dialogue based around this framework is an essential step to resolve this.

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