

Title: Causality, the critical but often ignored component guiding us through a world of uncertainties in risk assessment

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Abstract

The idea of uncertainty analyses, which typically involve quantification, is to protect practitioners and consumers from drawing unsubstantiated conclusions from scientific assessments of risk. The importance of causal modelling in this process – along with the inference methods associated with such modelling - is now increasingly widely recognized; yet organizations responsible for policy on uncertainty and risk in critical domains have generally ignored this body of work. We use recent guidance from the European Food Standards Authority on uncertainty analyses and the communication surrounding them and guidance on uncertainties by the Intergovernmental panel on climate change to illustrate the conceptual tangles that come from failing to acknowledge explicitly the necessity of causal reasoning in understanding uncertainties. We conclude that both organizations present guidance documents that specify how uncertainty can be quantified without any explicit reference to a principled framework or methodological approach that can quantify, and, from this, communicate uncertainties.

Introduction

To illustrate the critical issue of this article we begin with some definitions:

“**Hazard**: a biological, chemical or physical agent in, or condition of, food with the potential to cause an adverse health effect. **Risk**: a function of the probability of an adverse health effect and the severity of that effect, consequential to a hazard(s) in food.” (CAC, 2006).

These concepts are essential to **risk assessment**, which for many practitioners involves the following steps:

(i) hazard identification, - “The identification of biological chemical and physical agents capable of causing adverse health effects and which may be present in a particular food or group of foods” (WHO, 2009).

(ii) hazard characterization, - “The qualitative and/or quantitative evaluation of the nature of the adverse health effects associated with biological, chemical and physical agents which may be present in food. For chemical agents, a dose–response assessment should be performed. For biological or physical agents, a dose–response–assessment should be performed if the data are available” (WHO, 2009).

(iii) exposure assessment, “The qualitative and/or quantitative evaluation of the likely intake of biological, chemical and physical agents via food as well as exposure from other sources if relevant” (WHO, 2009) and,

(iv) combining (ii) and (iii) to determine how serious the risk is.

Note that, while probability is mentioned in the definition of risk but not hazard, what the definitions do have in common is the concept of causality (e.g., “food with the potential to **cause** an adverse health **effect**.” and “the probability of an adverse health effect and the severity of that **effect**.” and “**consequential** to a hazard”). So, imagine presenting a detailed and lengthy document on describing the uncertainties associated with each of the stages of risk assessment, and how to communicate those uncertainties, without acknowledging or outlining how uncertainties are directly related to causes, effects/consequences. It would seem odd given that the core definitions that are central to risk assessment are heavily dependent on the conceptual apparatus of causality. Unfortunately, documents from international organizations responsible for policy on uncertainty and risk in critical domains continue to ignore the central role of causality.

Organizations such as EFSA and the IPCC face incredible challenges in providing scientists guidance on how to conduct uncertainty analyses that are designed to expose limitation in knowledge at the time of carrying risk assessments, and how to communicate those uncertainties. This is fraught with inherent problems because, to date, the scientific community cannot agree either on 1) best practice for quantifying uncertainties; or 2) the most accessible way to communicate uncertainties to scientific and non-scientific audiences. However, both of these can be resolved, and have been resolved, with reference to statistical methods that combine causal analyses with Bayesian approaches to quantifying uncertainties. An increasing number of influential works now make very clear the central role of causality in risk analysis – notably (Cox, 2012) and (Pearl and Mackenzie 2018) - and role of causality in the communication of uncertainty (Fischhoff and Davis 2014). Once the language of causality is integrated into conceptualising uncertainties the gain is a

principled approach to characterising, and communicating uncertainties. In what follows we hope to first expose the core conceptual problems that prevents the translation of good scientific understanding of uncertainties into tackling social policy issues, and then spell out the conceptual apparatus needed to overcome them.

Quantifying and communicating uncertainties in regulation: EFSA draft guidelines on communication of uncertainty in scientific assessments (EFS 2018b)⁰ is an attempt to recommend useful methods to communicate uncertainty in scientific assessments to a variety of users, ranging from the lay public to well informed professionals. The concern is that transparency is lacking and thus there is a deficit in public trust and awareness. The EFSA guidelines identify a spectrum of uncertainty, from complete certainty at one end, to qualitative descriptions, then precise probabilities and finally uncertainties about probabilities at the other, thus offering scientists a choice of the “correct” way of expressing uncertainty to match the audience and the level of scientific knowledge available. Along the way such uncertainties might be turned into numbers; how this is done is obviously as important, or even more so, than the numbers themselves (although it is difficult recognize this important fact from reading the guidelines themselves). To illustrate the issue, here is what EFSA consider uncertainty to mean:

“In this document, uncertainty is used as a general term referring to all types of limitations in available knowledge that affect the range and probability of possible answers to an assessment question. Available knowledge refers here to the knowledge (evidence, data, etc.) available to assessors at the time the assessment is conducted and within the time and resources agreed for the assessment. Sometimes ‘uncertainty’ is used to refer to a source of uncertainty (see separate definition), and sometimes to its impact on the conclusion of an assessment” (EFSA 2018a, 2018b).

In EFSA’s guidance document (EFSA, 2018a) 28% of definitions presented in the glossary either make explicit reference to, or are associated with the term causality¹, compared to 19% which mention the term probability. In the other EFSA guidance document 0 **none** of the definitions in the glossary refer to terms that either explicitly refer to, or are associated with causality, and in (CAC, 2006) only 2% refer to the term probability. The important point to take away from this is that causality appears to be embedded in many terms that concern analysing uncertainties and reporting uncertainties, and yet nowhere in either documents is there any discussion of causality and its conceptual relevance in quantifying, interpreting, and communicating uncertainties in risk assessments.

EFSA are not alone in wanting to improve how uncertainty and risk is communicated – the IPCC’s communications on climate change are guided by similar ideas, as can be seen in the documents [Frey et al 2006] and [Mastrandrea et 2010] which set out the guidelines for reporting uncertainties in the IPCC 2006 and 2010 reports respectively . Yet, here is how the IPCC characterise uncertainty.

¹ These include, cause, conditional, cause of uncertainty/source of uncertainty, responsibility, control, controllability

“The AR5 [Assessment report 5] will rely on two metrics for communicating the degree of certainty in key findings: Confidence in the validity of a finding, based on the type, amount, quality, and consistency of evidence (e.g., mechanistic understanding, theory, data, models, expert judgment) and the degree of agreement. Confidence is expressed qualitatively. Quantified measures of uncertainty in a finding expressed probabilistically (based on statistical analysis of observations or model results, or expert judgment).”⁰

The IPCC document also makes only passing reference to causality² while discussing the analysis and communication of uncertainties in much the same way as EFSA do. In sum, both organizations present guidance documents that specify how uncertainty can be quantified without any explicit reference to a principled framework or methodological approach that can quantify, and, from this, communicate uncertainties. But, both organizations can be forgiven because, until quite recently, the state of play in the sciences and statistics did not suggest much in the way of progress on either the quantification of uncertainties or the communication of them (Osman, 2016; Osman, Heath, & Lofstedt, 2017).

A solution to the dilemma facing scientists and practitioners: Fortunately, there has been a quiet revolution in causal thinking that has made steady progress over the last few years (. The work of (Cox 2012) provided a detailed explanation of the role of causality in risk assessment, but there has been a recent revolution which originated in the most unlikely quarter: Artificial Intelligence (AI). The revolution has been spearheaded by ACM Turing award Judea Pearl, who has developed two key technologies crucial to the articulation, manipulation and quantification of causal thinking in reasoning (both human and machine): Bayesian networks and the calculus of causation.

Pearl’s first innovation - Bayesian Networks: Pearl argues that our uncertainty is more a function of our understanding of the causal processes that generated that data than it is a function of the statistical associations in the data, or the lack of data itself. In his recent bestselling book⁰, he points out that classical statistics only summarizes data – limiting us to answering questions about **association**, such as “What does a symptom tell me about a disease?”. It fails to answer the important causal questions that scientists seek answers to, namely about: **intervention**, such as “If I take aspirin will my headache be cured?”; or **counterfactuals**, such as “If I had not taken the aspirin would my headache still have stopped?”. Pearl provides a fascinating and powerful account of the evolution of causal thinking in science and statistics.

Pearl’s second innovation -: The calculus of causation, heralds the prospect of a revolution in the sciences because it shows that causation is central to human reasoning and hence the scientific method. He argues that the methods needed are simple and accessible: indeed, at its root is the idea of a simple causal diagram showing how variables interact. On top of this mathematical methods are introduced

² E.g. “For findings (effects) that are conditional on other findings (causes), consider independently evaluating the degrees of certainty in both causes and effects, with the understanding that the degree of certainty in the causes may be low” [IPCC, 2010, page 2].

to express uncertainty, determine how interventions might interrupt cause and effect and formulate answers to counterfactual “what if” questions. From this he constructs a three-layer causal hierarchy that underpins human causal reasoning. This can then be possibly developed to create a universal AI and which can be used clarify the relation between causal models and data.

Applications of Pearl’s ideas to practitioners: Pearl’s ideas on causal reasoning have been put to good use in risk and uncertainty assessment (Fenton and Neil 2018). For instance, Causal Bayesian networks have been applied to areas as diverse as agricultural interventions **Error! Reference source not found.**, system reliability evaluation **Error! Reference source not found.**, operational risk in finance **Error! Reference source not found.**, cognitive reasoning **Error! Reference source not found.** and legal argumentation 0. With a Causal Bayesian Network a scientist can represent their premises and assumptions, their data and opinions and the casual connections needed for the model to make sense. This provides a level of transparency and computational malleability unequalled by conventional statistics and impossible via the usual bureaucratic modes of articulation. Of course, they cannot provide a guarantee of correctness or predictive accuracy but what they do provide is coherence and a means of representing confirmatory and adversarial points of view in the causal model. To us this seems a critical part of promoting openness and trust. Guidelines such as those provided by the EFSA and IPCC encourage the production of “expert pronouncements on uncertainty”. But there is a danger they may do the opposite of what is intended because they hide the uncertainty surrounding the causal assumptions made about how the world works, either because these might be genuinely unknown or might reveal deeper uncertainties or, even worse, might reveal unuttered personal or organisational biases.

Conclusions:

Scientists and members of the public are much more likely to be persuaded about different types of risk by open argument and solid causal reasoning, accompanied by quantified uncertainties. People intuitively “reason causally”, and so the absence of causal reasoning to underpin an argument about uncertainty about specific risks will only raise suspicion that the argument serves vested interests. Clearly, continuing with a strategy that ignores the coming causal revolution will only lead to continued public distrust, a consequence the authors of uncertainty guidelines claim to wish to avoid. In conclusion to deal with uncertainty in the world we must take causality seriously and when communicating uncertainty, we should use causal, probabilistic, language since people understand the world in causal terms. When it comes to providing guidance on how to quantify risk and uncertainty, authorities should bear these points in mind so that they avoid making conceptual errors that impact practitioners, policy makers, researchers and the public.

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References

- CAC (2006) *Codex Alimentarius Commission Procedural Manual. 16th edition*. Joint FAO/WHO Food Standards Programme. Available at ftp://ftp.fao.org/codex/Publications/ProcManuals/Manual_16e.pdf (accessed 29-08-07).
- Cory W. Whitney Denis Lanzaova Caroline Muchiri Keith D. Shepherd Todd S. Rosenstock Michael Krawinkel John R. S. Tabuti Eike Luedeling (2018), "Probabilistic Decision Tools for Determining Impacts of Agricultural Development Policy on Household Nutrition", *Earth's Future* (Open Access) <https://doi.org/10.1002/2017EF000765>
- Cox, L. A. (2012). *Improving Risk Analysis*. Springer.
- EFSA Scientific Committee, Benford, D., Halldorsson, T., Jeger, M. J., Knutsen, H. K., [...] & Rychen, G. (2018a). Guidance on uncertainty analysis in scientific assessments. *EFSA Journal*, 16(1), e05123.
- EFSA Scientific Committee (2018b). Draft Guidance on Communication of Uncertainty in Scientific Assessments. *EFSA Journal*.
<https://www.efsa.europa.eu/sites/default/files/engage/180504.pdf>
- Fenton N.E, Neil M, Berger D, "Bayes and the Law", *Annual Review of Statistics and Its Application*, Volume (3) , 2016 (June), pp 51-77
<http://dx.doi.org/10.1146/annurev-statistics-041715-033428>
- Fenton, N. E., & Neil, M. (2018). *Risk Assessment and Decision Analysis with Bayesian Networks*. Boca Raton: CRC Press.
- Fischhoff, B., & Davis, A. L. (2014). "Communicating scientific uncertainty". *Proceedings of the National Academy of Sciences*, 111(Supplement 4), 13664–13671. <https://doi.org/10.1073/PNAS.1317504111>
- Frey, C., Penman, J., Hanle, L., Monni, S., & Ogle, S. (2006). Volume 1: General guidelines and reporting. *2006 IPCC Guidelines for National Greenhouse Gas Inventories, National Greenhouse Gas Inventories Programme, Inter-Governmental Panel on Climate Change*.
- Lagnado, D. A., N. E. Fenton and M. Neil (2013). "Legal idioms: a framework for evidential reasoning." *Argument and Computation*, 2013) , 4(1), 46-63) .
- Mastrandrea, M. D., Field, C. B., Stocker, T. F., Edenhofer, O., Ebi, K. L., Frame, D. J., Kriegler, E., Mach, K.J., Matschoss, P.R. & Plattner, G. K. (2010). Guidance note for lead authors of the IPCC fifth assessment report on consistent treatment of uncertainties. Neil, M., Marquez, D. and Fenton, N. E. (2010). "Improved Reliability Modeling using Bayesian Networks and Dynamic Discretization." *Reliability Engineering & System Safety*, 95(4), 412-425
- Neil, M., Marquez, D., and Fenton, N., Using Bayesian Networks to Model the Operational Risk to Information Technology Infrastructure in Financial

Institutions. *Journal of Financial Transformation*, 2008. 22: p. 1(CAC, 2006) 1-138.

Pearl, J., & Mackenzie, D. (2018). *The book of why: the new science of cause and effect*. New York: Basic Books.

Osman, M. (2016). Making a meal out of uncertainty. *Journal of Risk Research*, 1-4.

Osman, M, Heath, A., & Lofstedt, R. (2017). The problems of increasing transparency on uncertainty. *Public Understanding of Science*, 27, 131-138

World Health Organization. (2009). Principles and methods for the risk assessment of chemicals in food.

<http://apps.who.int/iris/bitstream/handle/10665/44065/?sequence=9>