Navigating Uncertainty: Understanding Stakeholder Decision-Making in Environmental Data Science

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This dissertation is submitted for the degree of Doctor of Philosophy

May 2025

School of Computing and Communications

Declaration

This thesis has not been submitted in support of an application for another degree at this or any other university. It is the result of my own work and includes nothing that is the outcome of work done in collaboration except where specifically indicated.

This thesis does not exceed the permitted maximum word count: approx. 62 000 words.

Kate Wright
29 May 2025

Abstract

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Increasing amounts of environmental data and use of alternative analysis techniques from statistics and computing are creating a paradigm shift for environmental studies. Tackling environmental problems requires trustworthy decisions, based on cross-disciplinary, open, and transparent research, with recognition that uncertainties in research need to be considered in more detail. Post-normal science, a concept developed in the 1990's, highlighted these features and recognised that single disciplinary applied science was no longer sufficient for the changes occurring in the natural environment, and that decisions required input from different stakeholders. More recently, the requirement of decision-makers for data-derived evidence to make decisions for alleviating environmental challenges has enabled environmental data science to emerge as a new research area. This cross-disciplinary study explores the production of scientific evidence for making decisions about environmental problems, particularly focussing on the different types of uncertainty along a data-to-decision pathway that could impact decision-making. Involving a multidisciplinary literature review, interviews and focus groups with environmental data scientists, and a historical case study looking at stratospheric ozone depletion, the study investigates the different types of uncertainties experienced by environmental data scientists and how these influence research used for making decisions. It also considers how scientists handle the challenges of conducting research at the boundary of science and policy, and finally considers the extent to which the concept of post-normal science provides a framework to guide environmental data science research. A new typology of uncertainty for environmental data science is presented which provides a summary of the uncertainties experienced by the different stakeholders at different points along the pathway. The study highlights the challenges of communication – particularly, how to communicate within cross-disciplinary research groups and communicating the research so that it is not misinterpreted. Building on these a generic communication framework is proposed to aid the environmental science community to communicate uncertainties to the different stakeholders involved with a particular environmental challenge.

Acknowledgements

The production of this thesis has involved the navigation of many uncertainties, from the complexity of the subject area, the Covid pandemic, and the uncertainty of life. I would like to thank all those who have helped me to achieve my magnum opus!

Specifically, thank you to:

My supervisors Professors Gordon Blair and Bran Knowles for their guidance, unwavering support when I lacked confidence and enduring the constant ‘plodding on’ that it has taken to produce this PhD.

Lauren Thornton, who helped me get to grips with qualitative research and endured my naïve ramblings.

To all those involved with DSNE who endured my questions with patience, especially Rachael Duncan. And to Simone for her assistance.

Rachael, Sarah and Alice for our Friday morning coffee-fuelled writing groups, when I should have been doing more writing than chatting.

All those who participated and willingly gave their time to be interviewed or to take part in focus groups, this thesis couldn’t have happened without you!

My examiners, Lucy Bastin and Emma Wilson, for an enjoyable viva, and for providing lots of helpful comments and feedback, all of which have definitely improved this final version of my thesis.

Lancaster University for providing funding for this PhD through the DSNE project.

And finally, many thanks for the support and encouragement from family and friends, especially Simon, Daisy, Rosie, Keenan, Mum, Dad and Claire.

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List of Abbreviations and Acronyms

AAOE	Airbourne Antarctic Ozone Experiment
AI	Artificial Intelligence
BODC	British Oceanographic Data Centre
CARE	Collective benefit, Authority to control, Responsibility and Ethics
CEDA	Centre for Environmental Data Analysis
CEEDS	Centre for Excellence in Environmental Data Science
CFCs	Chlorofluorocarbons
CRUISSE	Challenging Radical Uncertainty In Science, Society and the Environment
DAP	Dynamic Adaptive Planning
Defra	Department for Environment Food and Rural Affairs (DEFRA)
DMDU	Decision-making under Deep Uncertainty
DSNE	Data Science of the Natural Environment
EASOE	European Arctic Stratospheric Ozone Experiment
EIDC	Environmental Information Data Centre
FAIR	Findability, Accessibility, Interoperability and Reusability
FACT	Fair, Accurate, Confidential and Transparent
GAW	Global Atmospheric Watch
GBIF	Global Biodiversity Information Facility
IAM	Integrated Assessment Models
ICI	Imperial Chemical Industries
IO3C	International Ozone Commission
ISO	International Organization for Standardization
IPCC	Intergovernmental Panel on Climate Change
LOTUS	Long-term Ozone Trends and Uncertainties in the Atmosphere
M2D	Models to Decision
NASA	National Aeronautics and Space Administration
NERC	Natural Environment Research Council
NGDC	National Geoscience Data Centre
NOAA	National Oceanic and Atmospheric Administration

NOZE	National Ozone Experiment
OCF	Optimal Choice Framework
ODS	Ozone Depleting Substance
PDC	Polar Data Centre
PNS	Post-Normal Science
QA	Quality assurance
QC	Quality control
RIGOUR	Repeatable, Independent, Grounded in reality, Objective, Uncertainty-managed and Robust
SAGE	Scientific Advisory Group for Emergencies
SESAME	Second European Stratospheric Arctic and Mid-latitude Experiment
SORG	Stratospheric Ozone Review Group
STS	Science and Technology Studies
SPARC	Stratosphere-troposphere Processes and their Role in Climate
TOMS	Total Ozone Mapping Spectrometer
TRUST	Transparency, Responsibility, User focus, Sustainability and Technology
UEA	University of East Anglia
UNEP	United Nations Environment Programme
UV	Ultra-Violet
WCRP	World Climate Research Programme
WMO	World Meteorological Organisation

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1 Introduction

1.1 Introduction

In recent years the necessity for decision-making and policy formulation to address environmental challenges has become apparent. Such decisions require input from scientific research so this thesis explores shifts in scientific perspectives and practices that environmental research has undergone over the last five decades and examines how these have impacted decision-making procedures. A key aspect of these shifts is the provision of scientific evidence based upon an increasing volume of environmental data and the expansion of computing power and capabilities. These features are catalysing a paradigm shift within environmental science; new research methods, and methods not generally used by this discipline are being utilised to investigate and deliver evidence of the impact of environmental problems (Hey, Tansley and Tolle, 2009). Previously, environmental studies have focussed on understanding what, and why, changes are happening, so this development introduces new opportunities for environmental science to understand in more detail how the changes will affect life on Earth.

This introductory chapter provides a background to the thesis, along with its aims and objectives and an outline of the chapters to follow.

1.2 Background

It is necessary to explore shifts in scientific perspectives and practices that impact decision-making because contemporary complex environmental challenges present a problem for decision-makers[1]; they are often required to make decisions based on limited knowledge and about unknown future effects, i.e. *decision-making under uncertainty*. Areas of limited knowledge and unknowns need to be clarified and understood so they can be successfully navigated by all stakeholders, enabling decisions to be made on the most appropriate way to mitigate environmental challenges. Scientific evidence derived from data is increasingly becoming called upon to aid decisions to alleviate these environmental problems, thereby creating a linked pathway from the data to decisions. The ultimate goal is to ensure that the environmental data collected is used to its best advantage to make robust and trustworthy decisions. However, there are many steps and many people involved to get from one end of the pathway to the other.

The impacts of environmental changes often affect all members of society, so contemporary environmental challenges have changed the previously separate relationship between science, society and policy, leading to an overlapping of boundaries (see Figure 1). The people who are directly affected by changes to their environment offer local knowledge and personal experience. In addition to this, an increasing public engagement with science over the past 40 or so years has increased understanding and awareness of environmental challenges and led to a democratisation of science (Chilvers and Kearnes, 2020). The many voices and opinions feeding into the decision process is a complicating factor for those making the decisions, with the different experiences, understandings, and beliefs to consider alongside the scientific evidence. However, it should be noted that democratic decisions about an

[1] The term 'decision-making' (decision-maker) is often used synonymously with policymaking (policymaker); however, this study uses the term to cover anyone making a decision, i.e. any stakeholder involved in the process, including the scientists, public, industry, Government.

environmental problem are unlikely to be universal across the globe or extend to all members of society (Berg and Lidskog, 2018).

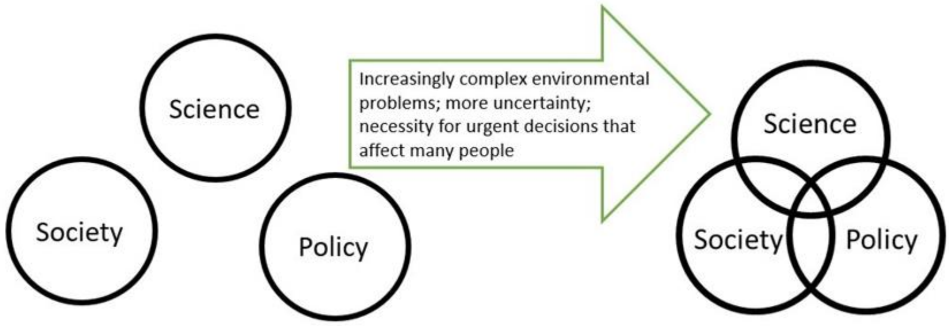

Figure 1. The changing relationship between science, society, and policy due to the decision requirements of environmental problems

This increasing societal influence on decision-making along with knowledge limitations and unknown future impacts creates uncertainty. This lack of certainty provides a potential excuse for inaction (Funtowicz and Ravetz, 1990), an avenue for confusion, disagreement and distrust in the scientific evidence (Ritchie, 2021), and an opportunity for the loudest voices to push their agenda (Oreskes and Conway, 2010). It is therefore imperative to understand what is causing any uncertainties so that, where possible, they can be explained, reduced, or managed, and so that the best mitigating decisions for an environmental problem can be taken. Ultimately, if ways of dealing with the uncertainties aren't identified, trust in scientific evidence will be eroded, decisive action will not be taken, and environmental problems could intensify.

In the early 1990s, Funtowicz and Ravetz (1990; 1991; 1993) recognised that environmental challenges were becoming more complex, that addressing them required policy intervention, and that conventional approaches to knowledge production were no longer suitable. Building on this, they developed their concept of post-normal science (PNS). They suggested that these challenges, created by dynamic environmental systems, where "facts [are] uncertain, values in dispute, stakes high and decisions urgent", prompted a new paradigm for the use of science (Funtowicz and Ravetz, 1991;

p138). ‘Normal’ science, described by Kuhn (1962) as problem solving, was no longer sufficient for these situations, particularly due to the uncertainties:

> *“Science was previously understood as achieving ever greater certainty in our knowledge and control of the natural world; now it is seen as coping with increasing uncertainties in these urgent environmental issues. A new role for scientists will involve the management of these crucial uncertainties; therein lies the task of quality assurance of the scientific information provided for decision-making.” (Funtowicz and Ravetz, 1990; p7).*

‘Normal’ (or applied) scientific research is still required to understand the environmental changes taking place; however, post-normal science looks to additional requirements needed to create robust evidence once the limits of normal science have been reached. As mentioned in the above quote one feature of PNS is assuring the quality of the research as a means of managing some of the uncertainties. When the PNS concept was developed Funtowicz and Ravetz (1990) noted that there was a lack of quality control or assurance in some areas of the scientific process, so they developed their NUSAP (Numerical; Unit; Spread; Assessment; Pedigree) scheme for reporting numbers. This provides a comprehensive scheme to judge and communicate the quality of quantitative evidence with the additional of the Pedigree category to cover the more qualitative aspects of the research (discussed further in chap 2). Additionally, different aspects of quality assurance can be judged by the inclusion of an ‘extended peer community’ (Funtowicz and Ravetz, 1993), defined by Ravetz (1999, p. 651) as “all those with a desire to participate in the resolution of the issue”. This recognises the expansion of the societal boundaries of science, and therefore acknowledges that all stakeholder knowledge is legitimate and should be incorporated into the decision-making process.

Post-normal science was developed in response to emerging environmental challenges that were global, had a long-term impact, needed urgent mitigating decisions and for which there was little relevant scientific data. The need to make decisions when there was little scientific evidence has led to the use of precautionary action. An example of precautionary action is the response to the depletion of the ozone layer in the 1980s, explored in more detail as a case study in chapter 5. This constituted a global environmental challenge that experienced a lot of uncertainty. However, urgent decisions were made before evidential data became available. More recently, science has become more heavily scrutinised, more evidence is required before action is taken, and there is less trust in expertise, partly driven by the questioning of expert advice by politicians and portrayal of scientists by the media (Barnes, 2005). Science has needed to adapt to these new requirements and perceptions so that scientific evidence is trustworthy and decisive action is taken. Looking backwards at the problem of stratospheric ozone depletion and gaining insights from the experiences of scientists involved with this challenge provides some areas of learning that could be applied to other contemporary environmental challenges. Additionally, as the scientific research provided unequivocal evidence for ozone depletion by CFCs and the policy process was hailed a success (see chapter 5) then it is beneficial to investigate if there are any experiences which could aid trust in science today.

The provision of robust evidence for environmental decision-making has changed established scientific practices, impacting on the uncertainty experienced by scientists. Rarely discussed is the effect of the changes on the scientists. When following the accepted scientific method, or ‘normal’ science, with which the scientists are familiar, they understand what is expected. However, when providing policy-relevant scientific evidence, the scientist is forced out of their disciplinary comfort zone, creating challenges within their research environment, such as working with other disciplines or using unfamiliar techniques. Additional to this, Funtowicz and Ravetz (1993; p740) argue that within normal science “values are unspoken”, however, as noted by Thorp (2023; p2) this remains a feature of all science – “[i]t has somehow become a controversial idea to acknowledge that scientists are actual people” going on to state “[s]cientists should embrace their humanity rather than pretending that they are a bunch of automatons who instantly reach perfectly objective conclusions”. The ‘value-ladenness’ of science and the effects of researchers' values on scientific research have been discussed by philosophers of science (Doppelt, 2007). This dichotomy between the objectivity and subjectivity of science appears at several points throughout this thesis. By maintaining a seemingly objective stance and refusing to be drawn into any political debate about environmental problems, scientists protect their credibility, remain trustworthy and in doing so maintain trust in science (Barnes, 2005). Credibility, like trust, is difficult to rebuild once lost.

The demand for data-driven evidence has led to the recent emergence of environmental data science methods which enhance environmental science research (Gibert *et al.*, 2018; Blair *et al*., 2019). Data science is the extraction of meaning from data (Blair *et al.*, 2019). Gibert *et al.* (2018; p7) provide a more detailed definition as; "the multidisciplinary field that combines data analysis with data processing methods and domain expertise, transforming data into understandable and actionable knowledge relevant for informed decision-making". They go on to conclude that; "[t]he potential of Data Science to advance our knowledge of the laws governing complex environmental phenomena is enormous" (Gibert *et al.,* 2018; p4). Thereby describing the application of techniques from computer science and statistics to the complex changes occurring in our natural environment, which has led to the emergence of environmental data science as a new research area (Gibert *et al.*, 2018; Blair *et al.*, 2019). Application of these data science methods to environmental data to support decision-making has created this rapidly developing interdisciplinary research area. These definitions refer to data analysis whereas this study incorporates the whole data lifecycle, including data collection/generation, processing/analysis, publishing/sharing, preserving, and re-using[2]. The development of the environmental data science discipline is a reaction to the need to make decisions about complex environmental challenges, enabled by the increasing acceptance of cross-disciplinary research and developments in computer-based methods and approaches.

The provision of scientific evidence based on data underscores the credibility of the scientists. However, it is vital to strike a balance and find ways of maintaining trust in science that scientists are comfortable with, and to ensure that the data-based evidence feeds productively into the decision process. The incorporation of different stakeholders

[2] See Research Data Lifecycle

along the data-to-decision pathway, along with the imperfect nature of environmental research creates the uncertainties highlighted by Funtowicz and Ravetz (1991) in the PNS approach. This thesis provides a holistic exploration of the uncertainties that can arise along the pathway from the data to a decision, providing a means to understand, and deal with, the potential sources of uncertainty affecting decisions.

1.3 Thesis aims and objectives

Within the context of environmental data science, the overarching aim of this multidisciplinary study is to explore how scientists navigate uncertainty in the production of scientific evidence. The thesis will focus on the different types of uncertainty along the data-to-decision pathway which could impact decision-making and will derive a new comprehension for the handling of uncertainty over the course of this pathway. Alongside these, the investigation of how uncertainty has been dealt with in the past provides insights which could be useful to incorporate into contemporary scientific research.

The aims of this thesis are to:

- Reflect on how uncertainty was dealt with in a historical environmental context to consider whether any lessons can be learnt and applied to contemporary environmental challenges.
- Explore the types of uncertainty experienced by environmental data scientists, in order to create a new typology of uncertainty for environmental data science.
- Explore the cross-disciplinary working practices of environmental data scientists to investigate the impact of uncertainties on these practices and the evidence for decisions that they produce, along with the challenges associated with cross-disciplinary collaborative research.
- Investigate methods to reduce uncertainty to enable robust decision-making, informing the construction of a framework to support the communication of uncertainty to aid decision-making, which will be of use to the environmental science community.

- Consider to what extent the concept of post-normal science provides a relevant framework for environmental data science.

In order to achieve these aims this thesis will:

- Synthesise multidisciplinary literature that discusses the use of scientific knowledge for decision-making.
- Synthesise multidisciplinary literature on uncertainty to identify concepts that are relevant for environmental data science.
- Analyse interview transcripts conducted with atmospheric scientists and decision advisors to understand the historical challenge of ozone depletion and the uncertainties that were experienced in this context.
- Analyse the transcripts from focus groups conducted with data scientists and environmental data scientists working on a collaborative research project in order to understand how statistical uncertainty is used for decision-making, and the challenges of collaborative research.
- Analyse transcripts from interviews conducted with environmental data scientists for the purpose of identifying contemporary uncertainties that they experience in their research, the ways in which these uncertainties influence their research and any ways to overcome these uncertainties.

These aims and objectives will explore the following research questions:

1. What are the different types of uncertainties experienced along the data-to-decision pathway, and how do these uncertainties influence environmental data science research used for making decisions?
2. What methods are currently used to navigate uncertainty, and what are the other techniques that could be adopted to enable an improved passage through uncertainty for decision-making?
3. Can an examination of historical environmental challenges and concepts that have evolved over the past 50 years yield valuable insights that can be harnessed to propel environmental data science into the future?

To summarise, this thesis is based on a multidisciplinary literature review, semi-structured interviews and focus groups. An underlying assumption of the study is that by understanding where the different uncertainties arise and how they may compound along the pathway from data to decision researchers will be able to provide better evidence for decisions.

1.4 Outline of thesis

This first chapter has introduced the motivation and background for the thesis. The remaining chapters are organised as follows:

Chapter 2 draws on literature to further explore the relationship between science, society, and policy decision-making. It investigates factors that influence decisions, introduces problems that uncertainty can create and considers how scientific practices have changed over time. It provides insights into the reasons for the changing nature of science, particularly over the past 50 years, and the opportunities and tensions that this presents. The chapter provides a foundation for why this study is necessary and situates uncertainty within scientific research literature.

Chapter 3 provides an in-depth overview of the multidisciplinary literature on uncertainty and picks out the concepts that are relevant for environmental data science. It draws heavily on uncertainty research within environmental risk literature, particularly the dimensions of uncertainty identified by Walker et al. (2003) to consider different uncertainties. By focusing on uncertainty, the chapter highlights the complexity of this concept to be navigated by environmental data scientists. This literature study informs the initial development of the steps along the data-to-decision uncertainty pathway.

Chapter 4 discusses research methodology which impacts the relationship between scientific and social scientific research. The chapter also describes the methods used in this study and explains how the three research studies interlink.

Chapter 5 presents a case study looking at the historical problem of stratospheric ozone depletion. Based on interviews with atmospheric scientists and those involved in the decision process, it explores the uncertainties experienced at this time and how they were handled. It also explores the experiences of the scientists when working at the science-policy boundary to understand their perspectives on this and investigates any insights that could be incorporated into contemporary environmental data science. Uncertainties discussed in this chapter mainly contribute to the communication and decision aspects of the data-to-decision pathway

Chapter 6 presents the results from focus groups held with data scientists from the Data Science of the Natural Environment (DSNE) project to discuss their background philosophies and perspectives on uncertainty. This collaborative group have a statistical or quantitative background, so this chapter focuses on understanding the meaning of uncertainty within statistics, and also the challenges of cross-disciplinary research. The chapter argues that without an understanding of uncertainty confusion and tension between stakeholder groups are inevitable. Uncertainties discussed in this chapter mainly contribute to the analysis aspect of the data-to-decision pathway.

Chapter 7 presents the results from the interviews conducted with environmental data scientists who are members of the Centre for Excellence in Environmental Data Science (CEEDS), a group of environmental data scientists from different environmental sub-disciplines. The research experiences of this group provide deeper insight into some of the uncertainties that emerged from the literature review discussed in chapter 3 and cover a wider range of data-related uncertainties than the previous chapter. This chapter also presents possible ways forward adopted by some interviewees but argues that without improvements to communication of uncertainty the challenge of 'decision-making under deep uncertainty' will continue. The uncertainties discussed in this chapter contribute to all aspects of the data-to-decision pathway.

Chapter 8 ties together all the previous chapters and proposes new tools to aid a step change in uncertainty navigation for environmental data scientists. Based on the uncertainties that have become apparent from the literature review and research studies, the chapter presents a new typology of uncertainty for the use of environmental data science for decision-making. This enables understanding of the different uncertainties experienced by different stakeholders along the data-to-decision pathway. To aid communication of uncertainty, emerging as an important feature from all the research studies, a framework for the communication of uncertainty for environmental data scientists is proposed, along with its application to two examples. This chapter also considers the relevance of the post-normal science framework to environmental data science, arguing that there are many features that are relevant but that societal changes since the development of this concept require PNS to evolve for contemporary science, particularly to include more emphasis on communication.

Chapter 9 concludes the thesis by providing a summary of the research and the contribution of this study. It also provides some possible areas of future research.

By the end of this thesis, environmental data scientists will have the tools to navigate the complex web of uncertainty experienced by different stakeholders, to understand and communicate policy-relevant scientific evidence.

2 The changing nature of science

2.1 Introduction

Scientific findings have formed the basis of new knowledge about life on Earth and beyond, but scientific practices have changed dramatically over the past 200 years. In the 19th century, science was based on empirical observations carried out by individuals to understand the world around us. However, modern environmental problems are complex, not all the different aspects and interrelationships can be known, and they often affect many members of society. This has changed the relationship between society and scientific research, due to increasing engagement with, and opinions about, environmental problems. Contemporary environmental challenges generally require decisions for mitigation, requiring cross-disciplinary collaborative research aided by advances in technology.

Scientific discoveries were portrayed as creating unquestionable facts, leading to the perception of certainty. It became increasingly evident that this was not the case. The scientific method and how knowledge is created was contemplated and critiqued by many philosophers, sociologists and historians (Ziman, 1996), eventually cumulating in the creation of the new disciplines of social studies of science, studies of scientific knowledge, and science and technology studies (Oreskes, 2019). Protagonists of these new disciplines have studied scientific practices (e.g. Karl Popper, Pierre Duhem, Steven Shapin[3]), questioning the actions of scientists and the certainty of the scientific evidence they provide (Latour, 1998). The realisation that scientific claims are not as certain as

[3] Many epistemologies of science have been proposed and discussed by philosophers, historians, and sociologists, see for example (Gieryn, 1995) and Oreskes (2019) for summaries.

portrayed has enabled people who have other viewpoints to question the trustworthiness of scientific claims, to sow seeds of doubt and/or to provide alternative explanations for scientific claims (Oreskes, 2019). These alternative viewpoints affect the level of certainty and understanding people have about the scientific information being presented, impacting the decision-making process.

The requirement for robust scientific evidence for making decisions motivated the recognition that scientific practices are out-of-date and need to change, e.g. the emergence of post-normal science (Funtowicz and Ravetz, 1990). Scientific evidence for making decisions to mitigate environmental problems is needed more than ever, so the challenge is how to create trustworthy and robust evidence. Scientific practices are changing, with increasing emphasis on cross-disciplinary teamwork and consensus between academic peers, which provide confidence in the research for making policy decisions. Cross-disciplinary research brings together groups of people with different expertise and resources to develop new areas of thinking (Mazzocchi, 2019). This mode of research has been encouraged to enable science to respond to problems that are too complex to be solved within one discipline (Treasury, 2006). Mazzocchi (2019) describes the creation of new disciplines when previously separate disciplines come together, providing systems biology as an example. Additionally, the promotion of ‘open science’ and transparency of data and research methods enables others to replicate analyses if they wish. All these are underpinned by the increasing amounts, and availability, of environmental data, which are being analysed using data science methods from statistics and computing to provide new insights into environmental science research. These developments provide new opportunities for the provision of scientific evidence for decision-making.

The chapter draws on an eclectic mix of literature from several research areas and explores examples of recent scientific phenomena to illustrate sources of tension between stakeholders, how uncertainties impact decision-making, and why the consideration of uncertainty is becoming increasingly important in scientific research. To put the changes to scientific practices over the past 50 years into context, this chapter starts with a brief look at how uncertainty had been discussed within science for the previous 200 years.

2.2 A brief history of uncertainty in science

The philosopher Auguste Comte (1798-1857) was the first to move away from the biases of religious doctrine and suggest that scientific method provided positive (reliable) knowledge through observation (Oreskes, 2019). This was the start of ‘positivism’, a philosophical theory that believes that scientific proof is provided by data, and is therefore objective, with no bias or input from the scientist themselves.

Nineteenth century scientists were generally gentlemen working alone, whose findings were accepted and trusted due to their social status (Passi and Jackson, 2018). These ‘wise men’ were seen as experts (Oppenheimer *et al.*, 2019) who presented unquestioned facts (Irwin, 2001). In his 1962 book *Structure of Scientific Revolutions,* Thomas Kuhn, concludes that day-to-day research is predominantly solving puzzles which he calls ‘normal science’ (Kuhn, 1962). Funtowicz and Ravetz (1990; p88) state that this creates “an illusory feeling of certainty in the permanence and truth of numerical facts and of scientific knowledge”. The theories, concepts and methods are trusted and taken for granted (Healy, 1999) and these operate within what Kuhn (1962) described as a ‘scientific paradigm’. However, once a problem can no longer be answered using standard methods or processes, scientists need to change their methodology and in doing so create a new paradigm, leading to a ‘paradigm shift’ (Kuhn, 1962).[4]

Latour (1998; p208) suggests that due to the significant increase in scientific progress over the past 150 years there has been a transition from agreed scientific facts to research, whereby “Science is certainty; research is uncertainty”. Sense about Science[5]

[4] A paradigm shift is a change to the concepts and practices within a scientific discipline in response to external forces that render the usual processes as inadequate.

[5] Sense about Science is an independent charity that promotes the use of good scientific evidence and transparency in the public interest: https://senseaboutscience.org/.

(2013) describe the scientific principles taught in school as ‘settled science’, indicating certainty and backing up Latour’s claim. This ‘settled science’ is based on ‘normal science’ whereby the puzzle (according to Kuhn above) has been solved. However, as our environment is not static further challenges emerge making further research necessary, until the ‘science’ is agreed. This research continues to produce new findings creating new uncertainties, for example Nowotny *et al.* (2001; p48) recognise that “[t]he emergence of new uncertainties has been stimulated by a growing recognition of the potential of science and technology to bring forth new ideas, concepts, methods, products and instrumentation”. In addition to uncertainties created by technological advances, the nature of the environmental research required has changed. Therefore, it is no longer a case of learning about a static natural environment, but how and why the environment is changing and predicting the impact of these changes. Many of the environmental problems that have emerged in recent decades have been human induced, such as pesticide use (e.g. DDT), stratospheric ozone depletion and climate change. Described as ‘wicked problems’ (Rittel and Webber, 1973) and ‘grand challenges’ (Omenn, 2006), many of these complex environmental phenomena have a global effect, creating the need for more complex global decision-making and changes to the way knowledge is created (c.f. Funtowicz and Ravetz, 1990; Nowotny, Scott and Gibbons, 2001).

Introduced in chapter 1, the development of post-normal science followed recognition that normal science was no longer sufficient to respond to the environmental problems outlined above. Table 1 summarises the differences between normal and post-normal science. Normal science is still required and functions within a solitary discipline using accepted scientific methods and new research is published in an academic journal which is validated by peer review. Whereas post-normal science is based on cross-disciplinary collaborations, incorporating the values and beliefs of multiple stakeholders, whose input provides an overview of the quality of the knowledge feeding into a decision. The difference between these is the disciplinary expertise of the individual/s assessing the quality of the knowledge presented. In addition to this is the speed of research validation, the writing of journal articles and subsequent peer review and publishing takes time, which is not available when urgent decisions need to be made. Incorporation of these tenets of post-normal science could provide a means of overcoming some of the uncertainties associated with complex contemporary environmental problems, especially when scientific research provides evidence for making policy decisions.

Table 1. Summary of the differences between normal and post-normal science (adapted from Strand, 2017 and Ainscough *et al.*, 2018)

Property	**Normal science**	**Post-normal science**
Knowledge source	Generated through established scientific methods and protocols	Incorporates different academic disciplines, alongside lay knowledge from non-academic stakeholders
Quality management	Data, methods and outputs are checked for errors, measurement problems, etc (QC - quality control) and required standards are followed (QA - quality assurance)	Inclusion of qualitative information (e.g. Pedigree in NUSAP) Oversight that QC/QA procedures are adhered to
Knowledge validation	Peer review by other experts within discipline	By all stakeholders, decision-makers, experts from other disciplines – make up an 'extended peer community'
Uncertainty	Aims to reduce ignorance; uncertainty represented by statistics	Many uncertainties due to the complexity and unpredictability of situation and stakeholder perspectives
Approach	Remains within single or closely related academic discipline	Incorporates a holistic approach to include all stakeholders affected by situation and decisions
Principles	Values rarely considered	Conflicting values and beliefs of multiple stakeholders
Risk	Remains within scientific paradigm, so little risk	Challenge has high stakes so decision could be risky
Decision urgency	Not related to decision-making	Research required for vital decisions to be made

2.3 Uncertainty and decision-making

2.3.1 Science for decision-making

The complexity of decision-making is further increased by uncertainties associated with environmental changes. Under ‘normal science’ or applied science, decisions are relatively straightforward and can be made by assessing risks using quantified uncertainties. However, Figure 2 shows that the ability to establish reliable and valid evidence based on empirical research becomes increasingly difficult as the level of uncertainty and the decision stakes rise. This creates the need for other ways of decision-making, such as the input from experts, and use of the post-normal framework. Once these options are exhausted ignorance becomes a major limiting feature (see also Funtowicz and Ravetz, 2013; Van der Sluijs, 2012), and alternative decision methods are required.

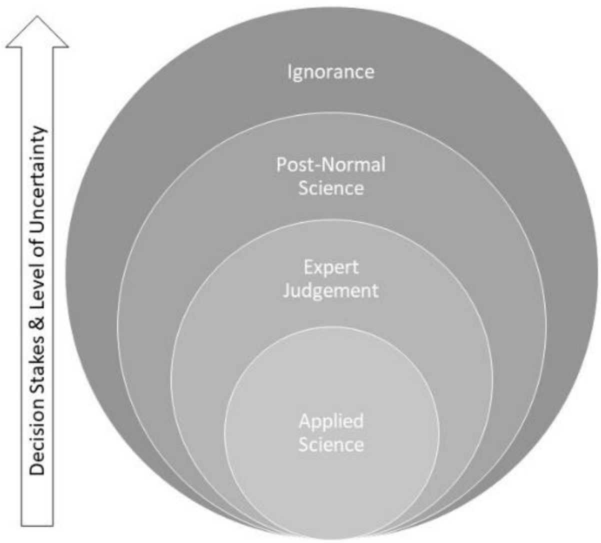

Figure 2. The changing requirements of science as the decision stakes and level of uncertainty increases (based on Funtowicz and Ravetz, 1993; p745)

The incorporation of scientific results, or involvement of scientific experts, into a decision-making process is not without problems. It can lead to a blurring of the boundaries between science and policy (Gieryn, 1995) whereby “scientific uncertainty and the pressures of decisionmaking [sic] lead to a forced marriage between science and politics" (Jasanoff, 1990). This can therefore create a dilemma for scientists who do not wish to be drawn into a politicised scientific debate (Jasanoff and Wynne, 1998; Irwin, 2001). This is explored in more detail in chapter 5 with regard to atmospheric scientists and ozone depletion.

Moreover, Krebs (2011) discusses several examples (pesticide drift and human health, badgers and bovine TB and alcohol-related harms) where scientific evidence has not been incorporated into policies due to uncertainties in the research or expert disagreement. However, Krebs (2011) also highlights that the political situation at the time of decision can also affect the outcome. Different stakeholders within a decision forum are likely to have different objectives and aversions to the uncertainties, as Beven notes "[d]ecision making is then about conflict resolution as much as about trying to maximise the benefits of a decision in some way under uncertainty" (Beven, 2010; p209). Palmer and Hardaker (2011; p4684) suggest that even with quantified estimates of uncertainty it is the values of the decision-makers and how they view the alternatives that sway their decisions and conclude "[i]n many situations, this may be a relatively simple economic matter". These examples show that there are many factors that influence decisions, but uncertainty in the scientific evidence can add to the difficulty of incorporating scientific research into decision-making.

Funtowicz and Ravetz (1990; p7) claim that "[p]olicy-makers tend to expect straightforward information as inputs to the decision-making process; they want their numbers to provide certainty". Obviously, this is rarely possible, so uncertainty can provide an excuse for inaction, Funtowicz and Ravetz (1990; p15) suggest that "[p]rocrastination is as real a policy option as any other, and indeed one that is traditionally favoured in bureaucracies; and 'inadequate information' is the best excuse for delay". Within the context of climate change, for example, Lewandowsky, Ballard and Pancost (2015; p1) state: "[p]oliticians and the public often appeal to uncertainty as an argument to delay mitigative action." This portrays a rather negative view of the likelihood of scientific results affecting decisions. However, there are examples of environmental decisions, such as the banning of stratospheric ozone depleting CFCs, which have been made based on little evidence (see chapter 5).

Wynne (1992b) provides one of the earliest discussions about uncertainty and environmental policymaking, and splits uncertainty into four different definitions:

- Risk – whereby the chances of a particular outcome are known[6]
- Uncertainty – the probabilities are unknown, but the system parameters are known
- Ignorance – aspects are unknown, but knowledge may be available from a different context
- Indeterminacy – not all parameters or their interactions are known

Stirling (2007; p312) divides 'incomplete knowledge' into risk, uncertainty, ambiguity and ignorance, using 'ambiguity' for Wynne's 'ignorance' and 'ignorance' for 'indeterminacy' (see Figure 3). These definitions reflect the range or level of uncertainty that can be experienced by stakeholders – a concept discussed further in the next chapter (see section 3.3.3).

As uncertainties become less quantifiable the outcomes become possibilities, and the decision-maker must decide whether these possible consequences require action or not (see Figure 3). However, when uncertainty can be quantified, the probability of a particular outcome can be calculated to provide an estimate of risk.

[6] For a detailed discussion on different types of risk see Althaus (2005) who provides a comprehensive summary of risk literature in different disciplines.

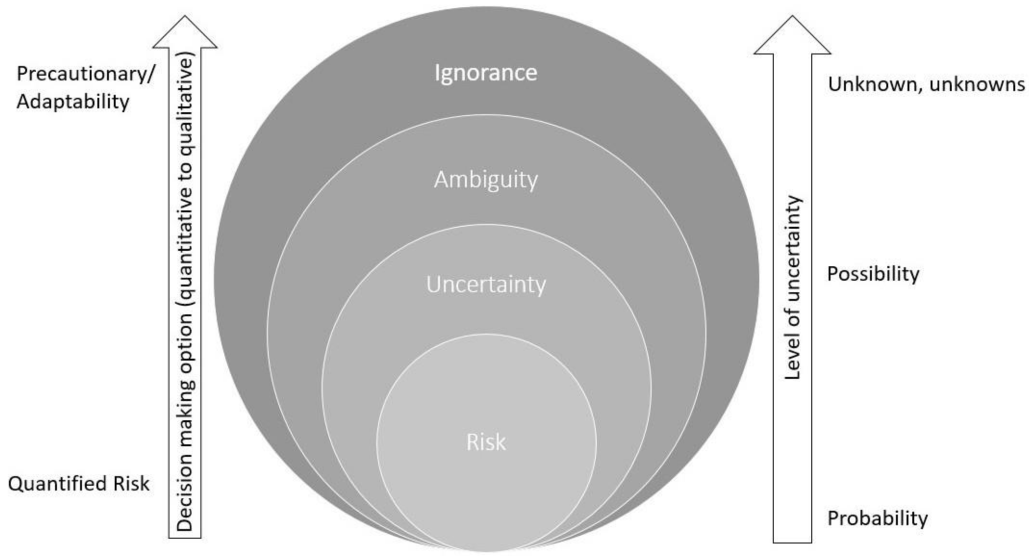

Figure 3. Modes of decision-making as the level of uncertainty moves from quantitative to qualitative based on Stirling's divisions of uncertainty (2007; 2010)

2.3.2 Decisions under risk

Economists appear to be the first thinkers to consider quantified uncertainty. Brady (2015) suggests that it was Adam Smith (1723-1790) in his 'Wealth of Nations' who first suggested a distinction between risk and uncertainty, although credit for this distinction is usually allocated to Frank Knight in 1921 (Knight, 2009). Krebs (2011; p4842) defines risk as "the probability of an event multiplied by its impact" going on to include uncertainty, stating that "uncertainty reflects the accuracy with which a risk can be assessed". A risk assessment is defined by the UK Department for Environment Food and Rural Affairs (Defra, 2011) as the "formal process of evaluating the consequence(s) of a hazard and their likelihoods/probabilities". Both of these quotes are referring to uncertainties that can be *quantified,* enabling analysis of the potential outcome/s which could be positive or negative, ie, a cost-benefit analysis.[7]

[7] A cost-benefit analysis is a systemised approach used to assess the disadvantages (costs) and advantages (benefits) associated with a particular decision, project, or policy. The goal is to decide if the benefits outweigh the costs, enabling more informed decision-making.

Applied science can provide quantified uncertainty information allowing a more straightforward assessment of risk, which enables the possible decision consequences to be known (Wynne, 1992; Stirling, 2007). There are various established methods available to a decision-maker to make a 'risk assessment' of the uncertainty. These include cost-benefit analysis, decision analysis, modelling, Bayesian and Monte Carlo methods and are assumed "to offer a comprehensively rigorous basis for informing decision-making" (Stirling, 2007; p309). Once a risk is assessed then it can be managed; risk management is defined as the "process of appraising options for responding to risk and deciding which to implement" (Defra, 2011; p6).

However, once it is no longer possible to quantify the risks, decision-makers must rely on other methods to formulate strategies for managing the risk (Defra, 2011). Alongside this they also need to decide on the amount of risk that an organisation is willing to be exposed to (i.e. their risk appetite). According to Knight (1921, referenced by Beven 2010) these are decisions under uncertainty, whereby the probabilities, and therefore consequences are not known (these unquantifiable uncertainties are sometimes referred to as Knightian uncertainties, after Frank Knight) and it is under these circumstances that 'post-normal' methods become more important. Although, as mentioned earlier, even these methods have their limits, but decisions still need to be made when uncertainties are deep, and ignorance abounds.

2.3.3 Decisions under ignorance

Ignorance is often described as 'unknown unknowns', after Donald Rumsfeldt's classic quote in response to a question at a news briefing on 12 February 2002 regarding the lack of evidence linking the Iraqi government with the supply of weapons of mass destruction to terrorist groups:

> *"Reports that say that something hasn't happened are always interesting to me, because as we know, there are known knowns; there are things we know we know. We also know there are known unknowns; that is to say we know there are some things we do not know. But there are also unknown unknowns—the ones we don't know we don't know. And if one looks*

throughout the history of our country and other free countries, it is the latter category that tend to be the difficult ones" (Rumsfeldt, Wikipedia, 2020).

One option for decision-makers when the level of uncertainty is very high due to ignorance, is called the Precautionary Principle. Taking a precautionary approach to environmental problems originated in German environmental policy in the 1970s. It became increasingly popular globally following the 1992 Rio Declaration on Environment and Development, which states: "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" (UNEP, 1992). However, the use of this approach as a policy tool is controversial. Advocates suggest that it promotes action based on early warning signs of a potential problem, even when there is ignorance surrounding many aspects of a problem (c.f. Harremoës, 2002). However, others (c.f. Gardiner, 2006) argue that it is ill defined, too vague and does not provide a sufficiently robust mechanism for decision-making. Other literatures provide a more nuanced account, with the usefulness of this precautionary approach becoming more appropriate as the level of uncertainty increases (Stirling, 2007). For example, Stirling (2007; p312) suggests use of the Precautionary Principle once the level of uncertainty passes 'risk' and the decision process is less straightforward, stating that "policy-making under uncertainty, ambiguity and ignorance should give the benefit of the doubt to the protection of human health and the environment".

The precautionary approach provides one option for decision-making under ignorance; however, alternative methods have been suggested which follow a more adaptive approach. Over the past 20 years, iterative decision-making processes enabling adaptation of decisions to incorporate new information as it arises have become established. This has led to the adoption and development of several decision-making approaches advocated by the Society for Decision-Making under Deep Uncertainty (DMDU; see Marchau *et al.*, 2019 for more details):

Info-gap Decision Theory is a non-probabilistic decision theory for prioritising alternatives and making choices and decisions (Ben-Haim, 2006, 2019). It aims to provide different options, or scenarios, to bridge the ‘info-gap’ between what is known and what needs to be known for a decision to be made. For example, it has been applied to conservation management of an endangered species to decide whether to cull predators or whether it is possible for the species to increase by reproduction (Hayes *et al.*, 2013).

Robust Decision-making (Lempert *et al.*, 2006) proposes that instead of using data and models to make predictions for decisions, they are used to create a range of future scenarios. Models are run to stress test proposed decisions, which are then subjected to visualisation and statistical analysis to help decision-makers identify the route/s that will help them achieve their future goals. This information enables decision-makers to identify, frame, evaluate, modify, and choose robust strategies which could be used for several possible future outcomes (Marchau *et al.*, 2019). For example, this has been applied to water resource management in particular locations using climate change scenarios to decide whether mitigations are needed for wetter or drier conditions (Dessai and Hulme, 2007).

Dynamic Adaptive Planning based on adaptive policy making (Walker, Rahman and Cave, 2001), this approach sets out the objectives and constraints for a plan for the short-term, as well as establishing a framework for possible future actions that can be adapted over time to meet changing circumstances (Walker, Marchau and Kwakkel, 2019). This has been applied in New Zealand to identify and plan for the impacts of climate change (Lawrence *et al.*, 2025).

Dynamic Adaptive Policy Pathways (Haasnoot *et al.*, 2013) incorporates Dynamic Adaptive Planning (DAP), adaptation pathways (Haasnoot *et al.*, 2012) and adaptation tipping points (Kwadijk *et al.*, 2010). Similar to DAP, this approach involves designing a plan consisting of a series of flexible and adaptable actions for the short, medium and long terms. The plan is monitored and if the future unfolds differently, or reaches a tipping point, then the plans are reassessed, and an alternative pathway adopted. For example, this has been applied to coastal flood risk management due to sea level rise. Mitigating pathways for the short-term (e.g temporary barriers), medium-term (e.g. storm-surge barriers) and long-term (e.g. permanent sea wall) are developed, along with the trigger points for reassessing a decision (c.f. Ramm, Watson and White, 2018).

These options provide alternative methods for environmental decision-making when decision-makers face deep uncertainty, or ignorance. The methods offer more flexibility than the precautionary principle, with the monitoring of situations allowing for decisions to be adapted or changed as more information becomes available, or to incorporate any additional affected communities.

2.4 Democratisation of science

Environmental challenges are not stand-alone issues: they affect and are affected by the actions of people. As mentioned previously, the increasing need for policy decisions, which affect all society, has increased public engagement with science (Wynne, 1992a). The public and stakeholders have become more actively involved in the production and/or evaluation of scientific knowledge, leading to a democratisation of science over the past 30-40 years (c.f. Beck, 1992; Berg and Lidskog, 2018). The traditional boundaries of knowledge production have been broken down by the incorporation of expertise from different sources, including those external to academia, enabling scientific evidence to be produced more democratically (Koskinen, 2017). This section explores how different stakeholders and communities engage with scientific research, both positively and negatively. In doing so, it incorporates one of the tenets of post-normal science, the inclusion of an 'extended peer community', which is the involvement of all stakeholders and therefore non-academic knowledge holders (Funtowicz and Ravetz, 1990; Meisch *et al.*, 2022). Scientific practices have developed in recent years to include the different knowledge producers that cross disciplinary and policy boundaries.

2.4.1 Mixing disciplines and teamwork

A contemporary picture of group research, which often crosses disciplinary boundaries, has replaced the historical image of a lone, detached scientist. In the UK, a paper in 2006 by HM Treasury provided an impetus for this, suggesting that interdisciplinarity should be central to the government's research strategy: "In order to maintain the UK's world-class university system, the [g]overnment is keen to ensure that excellent research of all types is rewarded, including user-focused and interdisciplinary research" (Treasury, 2006, referenced in Barry, Born and Weszkalnys, 2008).

Along with Funtowicz and Ravetz, other authors have recognised the changing needs of science, and incorporation of the different stakeholders to aid the decision process. Nowotny *et al.* (2001) describe going from working within one discipline to focusing on the need to combine disciplines to solve environmental issues as a move from 'Mode-1 science' to 'Mode-2 knowledge production'. Research incorporating multiple disciplines is vital for responding to environmental challenges and brings with it a demand for increased collaboration, diversity of research disciplines and incorporation of different methods to expand the research (Winter, Ferrario and Blair, 2020). These different types of knowledge production have also been described as "research science" and "trans-science" (or "policy science") by Carolan (2006).

Interdisciplinary/multidisciplinary/transdisciplinary are the terms used to describe the input from different knowledge producers and are often used interchangeably.[8] However, there are differences, Choi and Pak (2006; p359) have reviewed use of these terms in scientific literature and their definitions are summarised below:

- Interdisciplinary research combines knowledge from different disciplines with a collaborative end goal.
- Multidisciplinary research draws on knowledge from different disciplines but stays within the boundaries of the individual discipline.
- Transdisciplinary research integrates natural, social and health sciences holistically transcending each of their traditional boundaries.

[8] All these are relevant to environmental data science, so this thesis uses 'cross-disciplinary' as an encompassing term to include them all.

The nature of environmental challenges and the provision of evidence for decision-making creates a need for transdisciplinary collaborations. Bridle *et al.* (2013) expand the above definition of transdisciplinarity to also include the incorporation of non-scientific knowledge. The involvement of non-academic stakeholders in the research process reflects the 'extended peer community' of post-normal science, mentioned earlier (Funtowicz and Ravetz, 1990, 1993). Kates *et al.* (2001) call this 'sustainability science', which is the amalgamation of scientific and societal opinions. Lang *et al.* (2012) advocate utilisation of 'best available knowledge', which integrates knowledge from many sources, forming transdisciplinary knowledge production. An additional benefit to a collaborative transdisciplinary project involving all the stakeholders allows for the incorporation of co-design and co-production, so having that input enables a shared understanding of what can and needs to be achieved (Djenontin and Meadow, 2018), it also enables transparency and openness of the research – concepts discussed further in section 2.5.1. When the uncertainties of research are not transparent the scientific evidence can be questioned, potentially suggesting that aspects are being hidden and the message being communicated is biased. It provides a way for people who disagree with what scientists are presenting to create uncertainty, or doubt, in others.

2.4.2 Doubt

Contemporary environmental challenges which require mitigating decisions strengthen the overlap between science and society. The focus on the use of science for decision-making has led to concerns surrounding the trustworthiness and reliability of science (c.f. Ziman, 1978; Oreskes 2019). Hajer (2003; p180) discusses several environmental problems where the scientific results have been undermined, concluding that "scientific experts now face the problem that trust in their findings can no longer be assumed". Alongside this, uncertainties surrounding environmental phenomena can be messaged in different ways depending on the outlook or agenda of the messenger, potentially creating, or adding to, confusion and suspicion about scientific results.

Uncertainty in scientific results provides a basis to create doubt (Oreskes, 2010, 2018, 2019), and therefore affects how certain an individual feels about this information (this concept is discussed in more detail in chapter 3, section 3.3.3). In their book, ‘Merchants of Doubt’, Oreskes and Conway (2010) describe several examples where uncertainty has been used to perpetuate doubt by ‘scientists’ (people with a scientific background which provides them with credibility) and some political agencies in the USA. Unfortunately: “it is easy to take uncertainties out of context and create the impression that everything is unresolved” (Oreskes and Conway, 2010; p34). This therefore undermines and challenges scientific research even though results are already established by scientific consensus. These protagonists manage to gain some credibility for their arguments because:

> *“…they realized...that doubt works. And it works in part because we have an erroneous view of science. We think that science provides certainty, so if we lack certainty, we think the science must be faulty or incomplete. …. History shows us clearly that science does not provide certainty. It does not provide proof. It only provides the consensus of experts, based on the organized accumulation and scrutiny of evidence” (Oreskes and Conway, 2010, p267-8).*

An example of the problems created by a lack of transparency and uncertainty leading to doubt is the ‘Climategate’ controversy. In November 2009, emails and documents from the Climate Research Unit at the University of East Anglia (UEA), were released online — it is unclear whether the files were hacked or whether it was an inside job, with the police closing an inconclusive inquiry in July 2012 (Pearce, 2010). Prior to the release of documents, climate scientists at the Unit had received many Freedom of Information requests from sceptics and scientists from other disciplines. Additionally, collaborating climate scientists from other institutions had also received questions about their data, specifically regarding the historical temperature data they were using. The scientists at UEA were reluctant to release their data and methods so it was not possible for others to reproduce their research. Following the release of documents, the UEA scientists were accused of scientific fraud by the sceptics (although a UK parliamentary committee cleared them of this). Much of this climate research formed the foundations for the early Intergovernmental Panel on Climate Change (IPCC) reports, so this accusation created doubt about their results, which had a negative impact on the reputation of these assessments (Pearce, 2010). Scientists had produced what became known as the 'hockey stick graph' by combining historical data from dendrochronology and shipping records. This graph showed a sudden rise in recent temperatures, and its use was controversial — in Pearce (2010; p100) Mann (the US scientist responsible for creating the graph) admitted to Pearce "[g]iven its place in the IPCC summary with the uncertainties not even shown, we were a target from the beginning". The lack of transparency of uncertainty information, alongside the reluctance to release data, enabled the sceptics to sow doubt about the scientific methods used, the credibility of the scientists, and hence the resulting analyses.

In October 2012, BBC Radio 4 ('Climategate Revisited', 2012) reviewed the consequences of the incident and concluded that it made the media more dubious about what the scientists were saying and there was increasing pressure to include the viewpoints of climate change sceptics. The programme highlighted that there was loss of public trust in scientific practices due to the lack of openness and transparency. Mike Hulme (a climate scientist at UEA at the time), who was interviewed on the programme, agreed that it had led to a change in practice with an increase in the admission of uncertainties in papers increasing from 6% to 9% in the 3 years after Climategate.

Ravetz (2011) suggests that Climategate is an example of the scientists' attempting to carry out their 'normal' science within a 'post-normal' situation. Their research had policy implications, but the uncertainties were not considered. Unfortunately, this oversight led to the discredit of scientific authorities and the erosion of public trust in science (Lucas, Leith and Davison, 2015).

2.4.3 Post-truth

It is arguable that Climategate has contributed to suggestions that science is in 'crisis' (Saltelli and Funtowicz, 2017). Alongside this, problems of reproducibility (Ioannidis, 2005; Elliott, 2020), retraction (Steen, 2011), and "fraud, bias, negligence and hype in science" (Ritchie, 2021) are fuelling a change in the attitude of the public towards science, along with the anti-science attitudes of some politicians (Lynch, 2020).

Sismondo (2017) describes an emerging public psyche, labelled "post-truth". The Cambridge Dictionary definition of post-truth is "relating to a situation in which people are more likely to accept an argument based on their emotions and beliefs, rather than one based on facts" (McIntosh and Cambridge University Press, 2013). This reliance on emotions and beliefs to make a decision rather than expertise also indicates reduced respect for knowledge and experts. This changing perception of 'science', along with the increasing engagement of the public with science, has led to a more open debate about the use of scientific results by decision-makers and, more widely, whether there is an erosion of trust in scientific research (Ravetz and Saltelli, 2015). The impact of this, according to van der Bles *et al.* (2019; p2), is a reluctance of scientists and policymakers to communicate uncertainty as it "might have negative consequences, such as signalling incompetence, encouraging critics and decreasing trust". This therefore creates a dilemma, whether to communicate uncertainty in order to be transparent, at the risk of loss of reputation and trust, or to not communicate uncertainty which could also damage reputation and trust.

2.4.4 Trust

Trust is important to overcome doubt, it provides: "a spring board for the leap into uncertainty" (Luhmann, 1979, quoted in Talboom and Pierson, 2013; p91); and "an alternative to risk as a way of dealing with uncertainty" (Frederiksen, 2014; p130). Both of these authors are offering trust as a way to move forward when people face uncertainty.

There is a large body of multidisciplinary literature on trust and the distinct types of trust (c.f Talboom and Pierson, 2013), however, only those relevant for scientific research are considered here. The two that are important for this context are system trust and interpersonal trust:

System trust is that provided by stated rules that allow trust in a particular process, institution or person. In the research context this relates to trust in the scientific method which removes the direct connection to an individual (Talboom and Pierson, 2013).

Interpersonal trust is defined by Mayer *et al.* (1995; p712) as “the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party.” Talboom and Pierson (2013) highlight that the second part of this definition refers to vulnerability, risk and uncertainty, concluding that trust would be unnecessary if there were no risks. This type of trust is particularly important for the production and use of scientific evidence, which requires trust between all the individual stakeholders, especially, as discussed earlier, due to the increasing occurrence of transdisciplinary teamwork. In these circumstances the individuals are reliant on the validity of the science of others so as not to jeopardise their own reputation.

The classic model of interpersonal trust is provided by Mayer, Davis and Schoorman (1995) and proposes ability, benevolence and integrity as antecedents to trust - ability (trustee is able to do what the trustor needs), benevolence (trustee is caring and motivated to act in the trustor's interests), and integrity (trustee is honest and keeps promises) (McKnight, Choudhury and Kacmar, 2002). O’Neill (2018) suggests similar terms – honesty, competence, and reliability – which are required and are evidenced by providing as much transparency in the work as is relevant to the recipient so that they are able to judge the research as trustworthy. The cues described in the literature that allow trust, and hence provide indication of trustworthiness, are very similar, however, Corritore, Kracher and Wiedenbeck (2003) state that trust and trustworthiness are not the same because trusting someone or something is up to the individual, the trustor, whereas trustworthiness is a characteristic of someone or something that is to be trusted. The trustor needs to assess whether someone is worthy of their trust for the particular trust situation, i.e. it is context dependent. Luhmann states that trust can’t be demanded so the aim is to make oneself trustworthy and then the decision is up to the trustor (Baier, 1986). This leads to the question of how someone, or something, becomes trustworthy and how this can be conveyed to the prospective trustor. Driven by the scientific community and funders, scientific practices have adapted in response to the concern regarding the trustworthiness of scientific research discussed earlier, particularly relating to fraud and reproducibility in academic publishing (Grimes, Bauch and Ioannidis, 2018). The use of scientific research as evidence for decision-making has drawn attention to methods used to judge trustworthiness.

2.5 Creating trustworthy science

One problem when considering trust is who to place that trust in — expertise is not necessarily an indication that an individual is trustworthy (O'Neill, 2018; Gundersen and Holst, 2022), and as stated by Hajer (2003; p175) “scientific expertise is now negotiated rather than simply accepted”. This question of expertise formed the crux of the Climategate controversy discussed earlier. Some of the individuals questioning the work of the climate scientists were ‘experts’ but from different disciplines, which gave their scepticism some legitimacy. Alongside this, the lack of transparency by the climate scientists gave the impression that they had something to hide and were therefore untrustworthy. Some of the concepts important for creating trustworthy research are discussed below.

2.5.1 Transparency and open science

Recent years have seen a drive for scientific research to be more open, to promote reproducibility, innovation, and public understanding (Elliot, 2020). When discussing the foot and mouth epidemic of 2001 Krebs advocated openness with the public, concluding that “straightforward honesty about risk and uncertainty, coupled with clear advice for the public about their options, is the best policy” (Krebs, 2011; p4852). As this quote shows openness, i.e. transparency, is inextricably linked with communication. Communication of uncertainty in science and its effect on the recipient has been considered by many authors from different perspectives, e.g. on public trust (Hendriks and Jucks, 2020; Van Der Bles *et al.*, 2020), on decision making (Fischhoff and Davis, 2014). The way that uncertainty is communicated, e.g. using probability (Dieckmann, Peters and Gregory, 2015; Jenkins, Harris and Lark, 2018), or visualisation (Hadjimichael, Schlumberger and Haasnoot, 2024), impacts its interpretation. For example, Fischhoff and Davis (2014; p13664) state that “All science has uncertainty. Unless that uncertainty is communicated effectively, decision makers may put too much or too little faith in it” but raises the question of how to effectively communicate uncertainty. Bhatt *et al.*

(2020) suggest that communicating quantified uncertainties provide a mode of transparency for decision-makers. However, Dieckmann, Peters and Gregory (2015; p1281) state "just using numbers to express uncertainty is not enough to ensure accurate interpretation". They found that when uncertainty is communicated as a probability range based on statistical analysis, interpretation was variable and dependent on the numeracy of the audience. Therefore, concluding that additional explanation and information need to be provided to help the end user interpret the analysis as intended and decisions are correctly informed by the data (Dieckmann, Peters and Gregory, 2015). Hence, transparency is not just about providing quantification of uncertainty. Sometimes probability is translated into verbal-numerical formats, such as 'likelihood' based on percentages, but this also creates problems with understanding and interpretation (Jenkins, Harris and Lark, 2018), subsequently impacting on the individual's judgement of risk (Frewer, 2004). Visualisation techniques can be used to show quantified uncertainty but appear to be underutilised (Hullman, 2020; Hadjimichael, Schlumberger and Haasnoot, 2024), although the use of graphs and maps could make uncertainties more understandable (e.g. Rocchini *et al.*, 2011). An alternative to quantification is to communicate uncertainty as risk using storytelling (Shepherd *et al.*, 2018). Storylines aim to reframe risk in an event-orientated way providing a more realistic and understandable way to raise awareness of potential risks.

It is accepted that transparency of uncertainty leads to trust in scientific results (O'Neill, 2010; Thornton et al., 2021). However, in a review of research literature on the psychological effects of communicating uncertainty, i.e. producing a positive or negative response, Gustafson and Rice (2020) found the evidence to be inconclusive. For example, a study by Johnson and Slovic (1998) found that for some people the communication of uncertainty numerically indicated honesty and competency where as others saw the opposite. This inconsistency creates a dilemma for scientists of the potential negative consequences of communicating uncertainty transparently (van der Blaes et al., 2019).

Alongside transparency of uncertainties, the problems of replication and reproducibility in some areas of scientific research have fuelled the push for 'open science' (e.g. Royal

Society Science Policy Centre, 2012). Replication is the ability to repeat an analysis using the same method but using a different dataset, whereas reproducibility is having access to the same data and methods to produce the same results (Borges, 2022). Some scientific disciplines, e.g. psychology, have experienced scandals due to fraudulent manipulation and presentation of data, leading to a questioning of scientific practices and fuelling demand for transparency of the data and methods used so that studies can be replicated or reproduced (c.f. Munafò *et al.*, 2017; Ritchie, 2020). Another proposed incentive for openness is the increased access to other scientists' data and methods, which could encourage faster scientific innovation (Lowndes *et al.*, 2017; Cheruvelil and Soranno, 2018).

Munafò *et al.* (2017; p5) define open science as "the process of making the content and process of producing evidence and claims transparent and accessible to others". The Royal Society Science Policy Centre (2012; p16) define it as "open data (available, intelligible, assessable and useable data) combined with open access to scientific publications and effective communication of their contents". These definitions encompass changes happening to scientific practices. Generally, only a single analysis is reported in journal papers and, although peer reviewed, the authors can choose the results they report. Initiatives to reform scientific practices to make research more robust, such as large-scale replication studies, preregistration and registered reports, are increasingly becoming the norm in some disciplines, such as medicine and psychology (Munafò *et al.*, 2017).[9] In other subjects, authors suggest that multiple analyses of the same data should be carried out by different groups, this would then provide a range of results which can be used to show the full extent of possible uncertainties (e.g. Wagenmakers, Sarafoglou and Aczel, 2022; Breznau *et al.*, 2022).

The initiatives mentioned above focus on scientific practices to increase transparency of the data and methods. However, full transparency is complex, and philosophers of

[9] Preregistration is the registration of the hypotheses, methods, and/or analyses of a scientific study before it is conducted (c.f. Nosek *et al.*, 2018). Websites such as the Open Science Framework (http://osf.io/) and AsPredicted (http://AsPredicted.org/) are available to pre-register studies.

science have focused their attention to the lack of transparency about scientists' value judgments (Elliot, 2020). These are much harder to represent (Schroeder, 2021), but one way to overcome any biases that values could create is for several scientists to review research and provide a consensus about what they agree on.

2.5.2 Consensus

Oreskes (2004; 2019) suggests that the consensus of experts makes science more trustworthy. The rise of international scientific assessments to aid decision-making for global scale environmental issues reflects this. Expert peer groups regularly review current scientific knowledge for a particular environmental problem, providing an up-to-date summary of the relevant science to feed into the policy making process (Oppenheimer *et al.*, 2019). These reports provide a consensus of the panel of experts and indicate what they think is sufficiently settled to inform policy making (Oppenheimer *et al.*, 2019).

One example is the IPCC reports that started in 1990 and have continued every 5-6 years since. Scientists from all over the world have input, reducing bias from any one country (although it should be noted that not every country has scientists working in the relevant fields), who review new knowledge developed since the previous assessment (Oppenheimer *et al.*, 2019). Discussion of new research by experts aims to provide scientific agreement (where possible) in order to help overcome some of the scientific uncertainties arising from the research. Additionally, this process of review highlights areas of limited knowledge providing a direction for future research. Scientific assessments are discussed in chapter 5, which looks at the use of these as part of the legislative process to reduce stratospheric ozone depletion.

These reports are obviously a useful tool for policymakers. However, they are not without problems. For example, there is an ongoing debate about how uncertainty is represented in the IPCC reports (Aven and Renn, 2015). Communication of uncertainty was not considered formally until the third report (2001), when standard terms for probabilities, ‘likelihood’ and ‘confidence’, were introduced (Risbey and Kandlikar, 2007). Introduction of these terms also aimed to overcome some of the differences in opinions on evidence between the experts (van der Bles *et al.*, 2019) and are discussed in chapter 3. Additionally, a lack of consensus can be used by lobbyists to highlight uncertainties and undermine trust in the scientific research being used for making decisions.

2.5.3 Communication

An important way to create trustworthy science is through communication. This can range from making sure that everyone understands each other within a transdisciplinary group, to the transparent communication of results and uncertainties to all stakeholders, as discussed earlier. However, as van der Bles *et al.* (2019; p1) state: “[u]ncertainty is an inherent part of knowledge, and yet in an era of contested expertise, many shy away from openly communicating their uncertainty about what they know”. The first theoretical framework to manage scientific uncertainty for communication and policymakers was developed by Funtowicz and Ravetz (1990) following their recognition of the changing needs of science. Their system, NUSAP (Numerical; Unit; Spread; Assessment; Pedigree), helps with the communication of quantitative data. The Numerical, Unit, Spread and Assessment categories enable a quantitative evaluation, with Assessment relating to a formal method of uncertainty analysis (see chapter 3). The Pedigree category covers the more qualitative aspects of the research. It is expressed as a descriptive matrix which lists the levels of the research that are established through to those subject to ignorance, using column headings of ‘Theoretical structures’, ‘Data-input’, ‘Peer-acceptance’ and ‘Colleague consensus’. For example, for ‘Data input’ Funtowicz and Ravetz (1990; p140) go from experimental data to uneducated guesses through historic data, calculated data and educated guesses. Overall, the scheme provides a means to judge the quality of the research (Funtowicz and Ravetz, 1990).

A more recent framework for communication of epistemic uncertainty has been proposed by van der Bles *et al.* (2019) which identifies three objects of uncertainty – facts (data that can be verified), numbers (quantities that could have ambiguous definitions) and scientific hypotheses (distinguishing between theories and observations). Within their framework they also emphasise that it is important to consider who the audience is and what effect the communicator is aiming to achieve, ie. emotion, trust, behaviour, decision.

Prompted by the 'Climategate' incident, Landström *et al.* (2015) have looked at how 'experts' define uncertainty and how policymakers interpret scientists' communication of uncertainty within the context of climate change. They found that the definition of uncertainty depends on the disciplinary background of the interpreter, with those from a natural science background using quantitative terminology that the authors describe as a 'practice language'. Unsurprisingly they found that those with a social sciences background use more qualitative language. With regard to interpretation of uncertainty by policymakers, they discovered that many of their interviewees felt that, from their experience, policymakers understood scientific uncertainty.

Communication of scientific results and associated uncertainties by scientists to policymakers and the media (and therefore to the public) requires careful consideration. It is necessary to consider the values and beliefs of the stakeholders, the communicators and the receivers of the information, as well as other factors that can affect decisions. Unfortunately, decisions are not based simply on the quantifiable scientific uncertainties, there are many other qualitative and behavioural uncertainties that need to be considered.

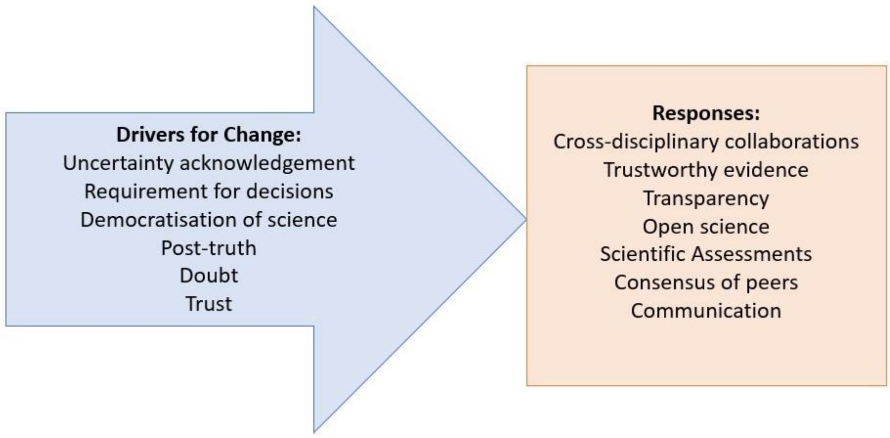

Figure 4. Summary to show the drivers for science to change and the responses, discussed in the chapter

These sections have described several reasons that have driven the changes to contemporary science, and the responses to these, summarised in Figure 4.

2.6 The data paradigm

The impetus for open science, described earlier, along with technical advances in data collection, retrieval and computing capabilities, has increased the availability of data and encouraged the incorporation of data science techniques into scientific research and is transforming environmental science. Data science is emerging as a new way to overcome some of the challenges and aid some of the responses, discussed in the previous sections. Data science is the extraction of knowledge from data using statistical and computational analysis techniques. Data is characterised in terms of its volume, velocity, variety (Laney *et al.*, 2001), with addition of veracity (Jagadish *et al.*, 2014), and value (c.f. Eidsvik, Mukerji and Bhattacharjya, 2015). This increasing importance of data within scientific research has been described as a paradigm shift. Computer scientist, Jim Gray, called this new era for science the '*Fourth Paradigm*', suggesting the previous three paradigms of science as empirical (observations), theoretical (models) and computational (simulations) (Hey, Tansley and Tolle, 2009).

2.6.1 Environmental data science

Environmental science consists of a mixture of academic disciplines and sub-disciplines covering the study of biospheres, water bodies and the atmosphere. Some researchers can remain within their disciplinary silo, although it is increasingly rare for an environmental scientist to take their own measurements and analyse the data without any input from others. Incorporation and analysis of data collected by others is now the norm due to the complex nature of contemporary environmental concerns. Environmental research is increasingly relied upon to provide evidence to inform decisions, providing an opportunity for the use of data science methods to interpret this data (Hey *et al.*, 2009).

Blair *et al.* (2019) note that variety and veracity are the two key features of data required for environmental data science. Environmental data is spatial and temporal; local and global. Availability of global spatial data varies enormously. In the Northern Hemisphere, particularly in Europe and North America, a lot of data has been collected due to the large amount of research funded in these regions over time (c.f. AbdulRafiu, Sovacool and Daniels, 2022). However, environmental problems are not limited to these locations and data for the global south is sparse, making it difficult to provide information to decision-makers in these countries, for example. In addition to these problems of data availability due to coverage, the veracity of data can be affected by the completeness of a dataset, i.e. whether data is missing and the reasons for this. These affect the quality of available datasets which are discussed in more detail in chapter 3.

Environment-related data is collected from many sources (c.f. Vitolo *et al.*, 2015), such as from in-situ instruments collecting long-term measurements, to short-term intensive field studies, via the use of simpler methods such as a camera to record a species of organism, or a thermometer to measure water temperature. A large amount of information is also gathered by remote sensing from satellites or drones, providing cost-effective data for atmospheric research or remote locations. Data collected from observations by the public, known as 'citizen science', are an increasingly popular source of research data (c.f. Heigl *et al.*, 2019). Often used to collect observational information on birds, insects or plants, it can provide a large amount of data which would probably otherwise not be available. Citizen science has been criticised for being inaccurate (Gardiner *et al.*, 2012), and inconsistent (Burgess *et al.*, 2017). However, Kosmala *et al.* (2016) conclude that scientific projects using data collected by non-experts should be judged on the project design and application, and not dismissed as substandard because the data is collected by volunteers. Citizen science provides a cost-effective method of obtaining a large amount of data, so depending on the type of data collected and potential errors in the data, it is still worthwhile. It also offers a mode of engagement and communication with non-specialists and the public about environmental issues.

All this heterogeneous data is then analysed using different methods, and sometimes fused together from different sources and used to identify "complex, hidden patterns useful for decision support" (Gibert *et al.*, 2018; p5). One feature of environmental science is the use of computer modelling, such as process models, which are used to understand the physical processes taking place, to make predictions about the future (forecast), and simulate past changes when observational data is not available (hindcast). Scenario models are an important tool for decision-making under uncertainty and are discussed in more detail in the following chapter, along with the uncertainties that are associated with modelling (see section 3.4.2). The increasing use of new data science approaches – digital twins, artificial intelligence (AI), machine learning – will advance interrogation of datasets by the detection of patterns and the ability to make probabilistic predictions for decision-making. For example, AI can improve accuracy and speed of forecasts, such as the six-month reduction in prediction times of Arctic Sea ice conditions which underpin early-warning systems (NERC, 2022). These approaches will aid data integration as they can be used across scales, large collections of data and environmental domains, enabling utilisation of the expanding volume of datasets to understand environmental systems, ultimately providing new insights for environmental science (NERC, 2022).

There are several initiatives that have been developed to aid transparency and collaboration for environmental data science, including:

- Data Centres
- Collaborative Research Environments/Virtual Laboratories
- Open-source resources

Data Centres provide online access to a wide variety of datasets. These can be managed repositories whereby datasets are only added after certain standards, usually relating to metadata, are met (discussed in more detail in chapter 3). Some examples of these in the UK for accessing data relating to the environment are:

- Atmospheric and earth observation: Centre for Environmental Data Analysis (CEDA)
- Marine environment: British Oceanographic Data Centre (BODC),
- Terrestrial and freshwater science, hydrology and bioinformatics: Environmental Information Data Centre (EIDC)

- Geological and environmental information on the surface and subsurface of Great Britain, and offshore: National Geoscience Data Centre (NGDC)
- Polar regions: Polar Data Centre (PDC)

Alternatively, they can be open repositories to which anyone, expert or amateur, can add data. Some examples include:

- Global Biodiversity Information Facility (GBIF)
- Animal tracking data (MoveBank)
- Citizen science-based community which uses open-source micro-sensors to measure fine particles in the air, as well as noise level (Sensor.Community)
- Maps created from surveys, aerial photos, satellite images (OpenStreetMap)

However, as anyone can add information to this type of repository the quality of the data is not as tightly controlled as managed repositories. Meyer *et al.* (2016) conclude that GBIF contains unreliable data due to taxonomic or geographical inaccuracies, missing data, or alien species. However, data showing alien species could be inaccurate due to misclassification or incorrect coordinates, or they could be indicative of an invasive species. There are elements of QA in GBIF, for example a quality flag will be applied if geographic location appears to be incorrect. Further investigation into the source of the data, if it is available, can provide an indication of accuracy, for example, if data has been deposited from an invasive species monitoring programme could indicate that the alien species data is not erroneous. These data centres still provide a source of useable data as long as any uncertainties are acknowledged. However, Contreras and Reichman (2015) conclude that the quality control of the data provided by the managed centres increases the value of the data.

Collaborative Research Environments/Virtual Laboratories have been designed to add functionality to data centres and incorporate software for data analysis and presentation (Thornton, Knowles and Blair, 2022). They provide a virtual collaborative workspace for groupwork in a research project, enabling more open science as all participants can see the assumptions and decisions made (Hollaway *et al.*, 2020).

Open-source resources for the environmental science community are increasingly being developed, e.g. The Environmental Data Science Book.

The incorporation and development of these data science initiatives requires resources - people, time and funds - introducing the necessity for pragmatism about what can be achieved with the resources available. Gibert *et al.* (2018) discuss the new professional job of 'data scientist', and the shortage of people with the required skills. The role has generally appealed to statisticians and software engineers; however, environmental data scientists are more often environmental scientists who are incorporating data science techniques into their research. In the UK, NERC has developed an online training programme (Data Tree) in research data management skills, aimed at PhD students and early career researchers.

Additionally, the push for openness and transparency in scientific research has focused attention on the control of data quality, as well as the availability and quality of the associated metadata. These features are important for assessing the level of certainty in results when researchers use secondary data. Some initiatives for data quality standardisation and tools to handle uncertainty are discussed in more detail in chapter 3, section 3.5.

2.7 Conclusion

This chapter draws upon a diverse body of literature to provide an overview of the evolution of scientific practices over the past couple of centuries, particularly in the context of the natural environment. In the past, science has been about discovery and has provided an illusion of certainty, however, the increasing complexity and severity of environmental problems currently being experienced has led to the recognition that scientific practices needed to change. The crux of the chapter is the use of scientific knowledge for making environmental decisions, and how uncertainties affect this. Policy action to control environmental problems has created an additional role for scientific research to provide evidence and possible solutions. However, the severity of uncertainty affects the decision-making process; when uncertainty can be quantified then decisions can be based upon risk. Once this is no longer possible, ignorance becomes dominant and unquantifiable uncertainty necessitates decisions grounded in possibilities, precaution, or adaptive approaches. Under these circumstances the scientific methods relied upon in the past are no longer suitable on their own for the requirements of decision-makers, creating a need for additional ‘post-normal science’ research methods. Reasons for this are:

- The convergence of science, society, and policy has ushered in a democratisation of scientific discourse, eroding the boundaries between distinct academic disciplines, non-academic knowledge holders, and public perspectives, which contribute additional unquantifiable uncertainties to environmental challenges, and affect decision-making.
- Uncertainty can be strategically employed to shape decisions, foster doubt to influence the beliefs of non-experts, and undermine trust in research findings. When scientific evidence is disputed, and expertise questioned, a desire for the research to be objective and therefore unquestionable is created.

Responses to these drivers of change highlighted in this chapter include:

- Strategies for reinstating trust in scientific evidence include transparency and openness and involvement of all stakeholders to combine knowledge, experience, and values from different sources to create transdisciplinary collaborations.
- The novel methods that environmental data science offers for analysing large, heterogeneous environmental datasets, which enables informed decision-making.

Interwoven through this chapter is the increasing acknowledgement of uncertainty within scientific research, its impact upon decision-making. It is now necessary to explore in more detail what uncertainty is, to understand why it requires creates challenges, and consider ways it can be handled.

3 What is uncertainty?

3.1 Introduction

This chapter takes an expansive view of uncertainty to provide a snapshot of the uncertainties relevant to environmental data science from the extensive multidisciplinary literature available. The chapter draws out different types of uncertainty to enable understanding of the complexity of this concept and provides an overview of the uncertainties to be navigated by environmental data scientists and other stakeholders. Uncertainties can be quantitative and/or qualitative with authors from different disciplines offering different typologies of uncertainty. A classic division of uncertainty is provided from environmental risk literature by Walker *et al.* (2003) who divide it into the dimensions of nature, location (source) and level. Further investigation of these dimensions provides a starting point for consideration of the different types of uncertainty experienced along the data-to-decision pathway – data, analysis, communication, decision and reception (understanding and interpretation) by stakeholders.

Once sources of, and reasons for, uncertainty are determined, methods to assess, reduce, or manage it can be considered in order to provide robust evidence for making decisions.

Building on this literature review the chapter concludes with four distinct divisions of uncertainty and shows how they feed into the data-to-decision uncertainty pathway. These form the basis for a new uncertainty typology relevant for environmental data science. This typology will be completed in chapter 8, incorporating data from interviews and focus groups discussed in subsequent chapters.

3.2 Introduction to uncertainty

Uncertainty is discussed within a variety of disciplines, with each providing different definitions and interpretations (e.g. Refsgaard *et al.*, 2007). Some consider uncertainty as an objective property of data and analysis (European Commission. Statistical Office of the European Union, 2019), others as a subjective judgement (e.g. Refsgaard *et al.*, 2007) or a limit to confidence in research outcomes (e.g. Kirchner *et al.*, 2021). Early studies focused on a narrow definition of uncertainty as a feature of data described using probability theory (c.f. Lindley, 2014). However, other studies consider uncertainty as a state of mind (Brown, 2004). These have been summarised by Parsons (2001; p11): "[u]ncertainty can be either an objective property of the information or it can be a subjective property of the observer". Morgan and Henrion (1990) distinguish between uncertainties that can be shown using probability and uncertainties that cannot, such as model structure and situations in which experts cannot agree upon the probabilities (Kwakkel, Walker and Marchau, 2010). These latter types of uncertainty are the hardest to handle (Morgan, 2003), and are sometimes referred to as 'deep' uncertainty (Lempert *et al.*, 2006), 'severe' uncertainty (Ben-Haim, 2006) or 'radical' uncertainty (Kay and King, 2020).

Consideration of uncertainties in environmental research and associated disciplines has proliferated over the past 40 years. Studies have looked at uncertainty in general (e.g. Smithson, 1989; Bevan, 2022); uncertainty in models (e.g. Beven, 2010); methods to reduce or control uncertainty (e.g. Morgan and Henrion, 1990); and uncertainty communication (e.g. van der Blaes *et al.*, 2019). Comprehensive reviews of literature looking at environment-related uncertainty have been carried out by Brown (2010), Skinner *et al.* (2014a), and Bevan (2022). These reflect the diversity of ideas about what constitutes 'uncertainty', with some authors avoiding using 'uncertainty' as the encompassing term, preferring such wording as 'imperfection of information' (Smets, 1997); 'imperfect knowledge' (Brown, 2010); 'imperfect information' (Parsons, 2001); 'state of confidence' (Brown, 2004), depending on the definition of uncertainty they prefer. Literature provided by environmental protection and regulatory agencies to aid scientific or environmental decision-making use definitions of uncertainty which refer to gaps in knowledge; for example, "limitations in knowledge about environmental impacts and the factors that influence them" (Defra, 2011): “our inability to know for sure” (US EPA, 2010) or “known impacts and unknown probabilities” (EEA, 2007).

One feature which is highlighted by these definitions, is that much of the discourse about uncertainty suggests that uncertainty is a negative state, such as the use of the ‘uncertainty monster’ metaphor introduced by Van Der Sluijs (2005). However, McCain and Kampourakis (2019) argue that rather than being detrimental to science, uncertainty is needed to help it advance, with new evidence and revision of theories to increase understanding.

These different definitions of uncertainty, or limited knowledge, have led many authors to develop typologies[10] to show relationships between different types of uncertainty occurring in their disciplinary area (Bevan, 2022).

3.3 Typologies/taxonomies/ontologies/frameworks

The number of different typologies indicates the complexity of uncertainty; how it is understood, defined and its different components (Walker *et al.*, 2003). There are, therefore, many different typologies and theories of uncertainty, relevant to different contexts – e.g. hydrological modelling (c.f. Beven, 2016); climate modelling (c.f. Parker, 2010); ecology (c.f. Regan *et al.*, 2002); artificial intelligence (Krause and Clark, 1993). Early typologies (e.g. Howell and Burnett, 1978) were based on probability theory (referenced in Smithson, 1989). A psychological dimension is provided by the classic study of Kahneman and Tversky (1982) on the ‘Variants of Uncertainty’ who divide uncertainty into external (probability) or internal (cognitive) which also reflects the objective/subjective divide (Smithson, 1989).

Several authors have reviewed the proliferation of typologies. Skinner *et al.* (2014a) reviewed all those they found relating to environmental risk assessment (n=30); Doyle

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[10] Framework/taxonomy/classification are used interchangeably with typology in the uncertainty literature, depending on the discipline.

et al. (2019) those relating to communication of uncertainty (n=111); and Bevan (2022) all literature on uncertainty related to studies on environmental change (n=156). Each of these papers include a comprehensive list and summary.

Many recent typologies of uncertainty developed for environment-related contexts are influenced by the framework of Walker *et al.* (2003), created for model-based decision support. This framework divides uncertainty into the dimensions of *nature*, *location* and *level*, and are summarised in Figure 5. These are discussed in more detail in the following sections and provide the reference terms to be built on through the thesis.

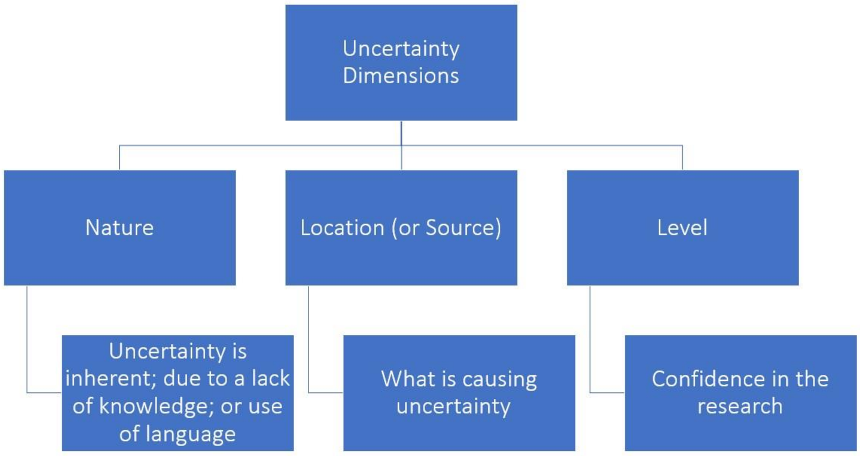


Figure 5. Summary of uncertainty dimensions for scientific research identified by Walker *et al.* (2003)

3.3.1 The *nature* or type of uncertainty

The classic division of scientific uncertainty is into two different types – aleatory and epistemic – described as the *nature* of uncertainty (e.g. Morgan and Henrion, 1990; Walker *et al.,* 2003). This division was first suggested by Hacking (1975) in relation to types of probability (cited in Bevan, 2022). In addition to aleatory and epistemic, linguistic uncertainty is also sometimes included by some authors as a distinct uncertainty type (Regan *et al.*, 2002; Beven, 2010) and therefore included in this section as another *nature* distinction for completeness.

Aleatory is used to describe uncertainty that occurs due to unpredictable variability. This could be due to 'noise' (Beven, 2010), natural variability in a system (Bedford and Cooke, 2001), the randomness of human behaviour (van Asselt and Rotmans, 2002) or even lack of knowledge about the future (van der Blaes *et al.*, 2019). As it is an inherent feature, it is generally described as unreducible (van Asselt and Rotmans, 2002) and can be quantified by probability (Aguirre *et al.*, 2013) or expert opinion (Bedford and Cooke, 2001). These different definitions are reflected in the synonymous words used by the different authors (highlighted in Table 2), which often depend on disciplinary background.

Epistemic is used to describe uncertainty created by limited knowledge and therefore could be reduced or even eliminated with further study, although further study could reveal additional areas of ignorance producing additional unexpected uncertainties (Skinner *et al.*, 2014a).

These two distinctions have been noted by many authors, with aleatory and epistemic the most frequently used words. Table 2 shows the alternative wording used by authors to show the distinction.

Table 2. Examples of synonymous wording used for aleatory and epistemic uncertainty

Aleatory	Hacking 1975; Bedford and Cooke, 2001	**Epistemic**
External	Kahneman and Tversky, 1982	Internal
Physical	Vesely and Rasmuson, 1984	Completeness
Stochastic	Helton, 1994	Subjective
Variability	Hoffman and Hammonds, 1994	Knowledge-based
Randomness	Bevington and Robinson, 2003	Systematic
Variability	van Asselt and Rotmans, 2002	Limited knowledge
Irreducible	Kirchner *et al.*, 2021	Reducible
Stochastic	Kirchner *et al.*, 2021	Epistemic
Ontic	Petersen, 2006	Epistemic
Objective	Natke and Ben-Haim, 1997; Smets, 1997	Subjective
Ontological	Derbyshire, 2020	Epistemological

Linguistic uncertainty can occur due to the lack of definition of a problem or context (Regan *et al.*, 2002; Grubler *et al.*, 2015) or due to language ambiguity where wording could have more than one meaning and it is unclear which is meant (Walker *et al.*, 2003). Contradictory wording creates additional confusion and uncertainty (Walker *et al.*, 2003). Language uncertainty can be problematic within cross-disciplinary research, for example, even the word 'data' creates a language ambiguity within environmental science — as well as being used for empirical information, output from process models is also described as data by many environmental modellers. 'Ambiguity' can be used synonymously to cover uncertainties in language and is used to encompass other language uncertainties. These include;

- wording that is too general — described as underspecificity (Regan *et al.*, 2002) or imprecision (Parsons, 2001)
- indistinct terminology or vagueness (Regan *et al.*, 2002; Ascough II *et al.*, 2008)
- lacking necessary information or incompleteness (Parsons, 2001)
- contradictory information or inconsistency (Parsons, 2001).

Some authors with a more statistical view of uncertainty do not agree that language should be included as an uncertainty (e.g. Bedford and Cooke, 2001). Kirchner *et al.* (2021) argue that as it is possible to reduce linguistic uncertainty with better clarification and communication, it fits better as a source of epistemic uncertainty, rather than a distinct uncertainty type.

3.3.2 Location (source) of uncertainty

Once the nature of an uncertainty has been determined, the *source,* why or where the uncertainty is occurring, can be considered. Although originally described as *location* by Walker *et al.* (2003) *source* is often used synonymously (Kwakkel *et al.*, 2010). As *location* was originally used by Walker *et al.* (2003) for their context of modelling, this thesis will use *source* as it encompasses a wider range of uncertainty origins. Nature and source can appear to be similar, however, the nature dimension affects how the uncertainties are handled. Aleatory uncertainties can be quantified using probability, whereas there are many methods to deal with epistemic uncertainty (Walker *et al.*

2003). Sources of uncertainty, such as data, analysis, and behaviour, are epistemic uncertainties. As these are relevant to environmental data science and form the basis of uncertainties along the data-to-decision pathway, they are discussed in more detail in section 3.4.

3.3.3 Level of uncertainty

The third dimension of uncertainty discussed by Walker *et al.* (2003) is the *level* of uncertainty, which they describe as going from determinism to total ignorance. It can be interpreted as a feature of the research, or the level of uncertainty experienced by an individual (Parsons, 2001). Kwakkel *et al.* (2010; p307) define it as “the assignment of likelihood to things or events” and is used to show the range of uncertainty – from risk to ignorance – discussed in chapter 2. These levels of uncertainty are particularly relevant when it comes to making decisions, as they show the *severity* of uncertainty that judgements and decisions are made under (Bradley and Drechsler, 2014).

Brown (2010) defines uncertainty as a “level of confidence”, using a broad definition of confidence as the degree of trust or conviction in knowledge, and includes “statistical confidence”. Confidence varies from certainty that something is correct, erroneous, or irrelevant to acknowledging that nothing useful is known – all of which contribute to the level of uncertainty (Brown, 2010). However, this definition states that confidence requires a state of awareness, thereby excluding ignorance.

The inclusion of ignorance as part of uncertainty is controversial. Some authors, such as Smithson (1989), Bonissone and Tong (1985), Bosc and Prade (1997), consider uncertainty as an element of ignorance, with Smithson (1989; p9) stating that “uncertainty…occupies a special position as one of the most manageable kinds of ignorance” and that “uncertainty is not as broad a concept [as ignorance] even though it is the home of probability theory and several other newer normative approaches to ignorance”. However, Kirchner *et al.* (2021) note that other authors include ignorance as a feature of uncertainty, such as Walker *et al.* (2003) (recognised and total ignorance) and Faber *et al.* (1996) (accepted ignorance). These differences reflect the background discipline of the author, with those who prefer a narrower definition of uncertainty from a mathematical/statistical background, and those using a wider definition open to qualitative uncertainties.

Table 3 provides a summary of some of the different terminology and definitions of uncertainty levels found in the literature. All show that authors recognise that uncertainty that can be experienced along a spectrum, from low to high.

Table 3. An example of the synonymous terminology for the different levels of uncertainty from relevant literature

Authors	**Levels (and definitions)** Disciplinary division: orange – environmental risk assessment; green – policy				
	Low uncertainty				**High uncertainty**
Walker *et al.*, 2003	Statistical uncertainty		Scenario uncertainty	Recognised ignorance	Total ignorance
Krayer von Kraus, 2005 (cited by Skinner *et al.*, 2014b)	Known probabilities		Unknown probabilities		
	Known outcomes	Unknown outcomes	Known outcomes	Unknown outcomes	
Kwakkel *et al.*, 2010	Level 1 (shallow uncertainty)	Level 2 (medium uncertainty	Level 3 (deep uncertainty)	Level 4 (recognised ignorance)	
(Skinner *et al.*, 2014b)	Determinacy	Statistical	Scenario	Ignorance	Indeterminacy
(Skinner *et al.*, 2014a)	State 1: knowing a lot	State 2: knowing the probabilities	State 3: knowing the outcomes	State 4: knowing a little	State 5: not knowing
Wynne, 1992b	Risk		Uncertainty	Ignorance	Indeterminacy
Stirling, 2007	Risk	Ambiguity		Uncertainty	Ignorance
Bradley and Deschler, 2014	Mild uncertainty (judgement is possible)		Severe uncertainty (partial judgment possible)	Ignorance (no information to make a judgement)	

The level of uncertainty or confidence experienced varies by stakeholder. In 1990 MacKenzie (1990, 1998) proposed a certainty trough (see Figure 6) which shows that the knowledge producer has a higher level of uncertainty as they are aware of the limitations of their research. If these are not communicated, then the knowledge user will be unaware of these uncertainties and will feel more certain about the results. However, moving away from the origin of the knowledge a stakeholder has less connection to the information so their uncertainty increases, as they are less likely to understand the research process or perhaps the disciplinary language used.

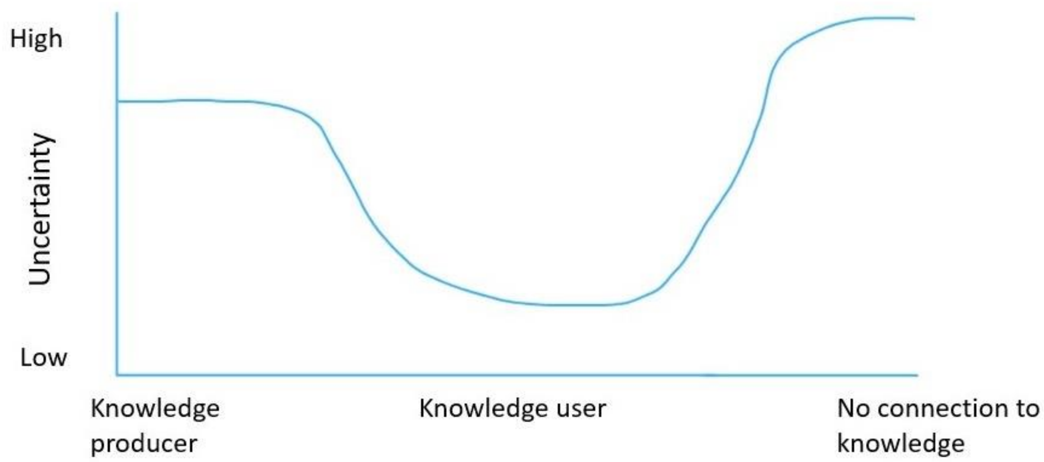
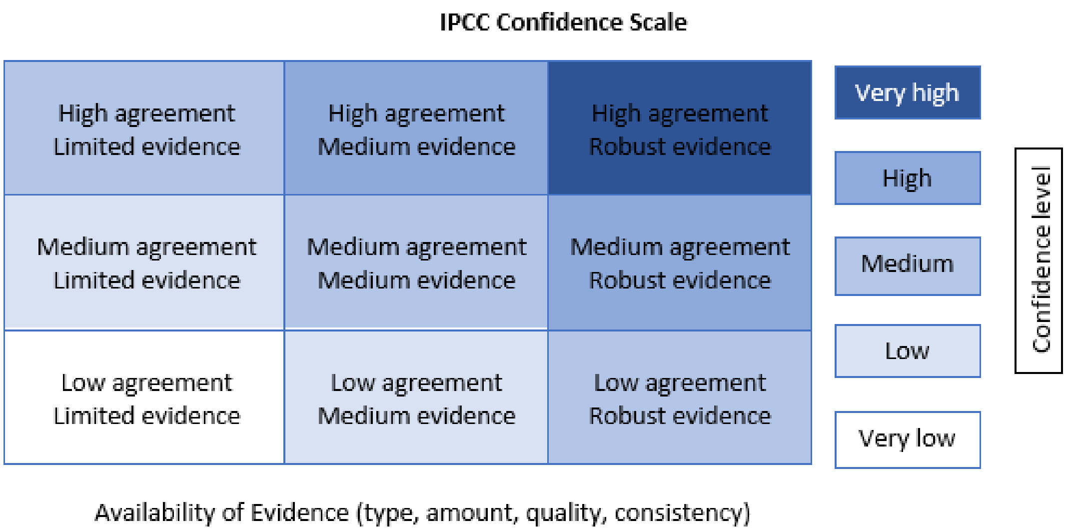


Figure 6. Schematic of Mackenzie's certainty trough (adapted from Mackenzie, 1990; p372; 1998, p325)

Although originally designed for the context of antiballistic missile technology, this study is highly cited in other contexts (e.g. climate change, c.f. Shackley and Wynne, 1996, Lahsen, 2005; Covid-19, Pearce, 2020). Subsequent studies (Lahsen, 2005; Pearce, 2020) argue that the shape of the trough is context dependent and does not capture all the potential nuances of scientific research. Pearce (2020) considers it in relation to the Covid-19 pandemic and concludes that there is a potential conflict of interest because the same people assessing the research and advising Government (e.g., members of UK's Scientific Advisory Group for Emergencies, SAGE) also carried out much of the research. This blurred the boundary between knowledge producer and user, leading to the reduction in uncertainty acknowledgment and therefore flattening the trough in this context.

Representation of the level of uncertainty has been introduced into scientific assessment reports. With regard to climate change and its potential consequences, an uncertainty language framework was introduced into the IPCC assessment reports in 2001 following criticism that uncertainties were not included (Mastrandrea *et al.*, 2010).



IPCC Likelihood Scale	
Term	**Likelihood of the Outcome (probability)**
Virtually certain	99-100%
Extremely likely	95-100%
Very likely	90-100%
Likely	66-100%
More likely than not	50-100%
About as likely as not	33-66%
Unlikely	0-33%
Very unlikely	0-10%
Extremely unlikely	0-5%
Exceptionally unlikely	0-1%

Figure 7. Confidence and likelihood scales used by the IPCC (adapted from Mastrandrea *et al.*, 2010; p3)

The IPCC now describe the uncertainties by providing assessment of ‘confidence’ and ‘likelihood’ (see Figure 7). Confidence reflects a qualitative assessment based on author agreement and likelihood is used for uncertainties that can be quantified (Mastrandrea *et al.*, 2010). However, this framework has been criticised for lacking clarity and inconsistent implementation between working groups. It has been revised before each of the Third, Fourth and Fifth Assessment Reports (Janzwood, 2020). A study by Budescu *et al.* (2014) concluded that the subjectivity of the terms is problematic as they are open to an individuals' interpretation, with people generally tending to underestimate high probabilities and overestimate low probabilities.

3.3.4 A relevant typology for environmental data science

The previous three sections have discussed the three dimensions of uncertainty defined by Walker *et al.* (2003). Using these dimensions and a review of thirty typologies, Skinner *et al.* (2014a) created a new typology for environmental risk assessment (shown in Figure 8). As there is overlap between assessment of environmental risks and the application of environmental data science, this is included here as the most relevant typology to this thesis, and aspects of it have been incorporated into the new typology for environmental data science resulting from this thesis. The overlaps are due to the use of environmental data to ascertain the risks to make risk-related decisions; environmental data science provides additional insights to data by the application of data science methods.

In this typology, the natures and sources of uncertainty are shown in the inner sections, with the levels shown in the outer circle. This provides a comprehensive typology including sources of epistemic uncertainty, which few other authors consider in as much detail. An expanded and more complex typology, based on a larger literature study, is available in Skinner *et al.* (2014b).

The sources of epistemic uncertainty – data, model, human, language – shown in this typology are highly relevant for environmental data science. The initial categories for investigation of uncertainty sources for this thesis were extracted from this for further exploration and expansion.

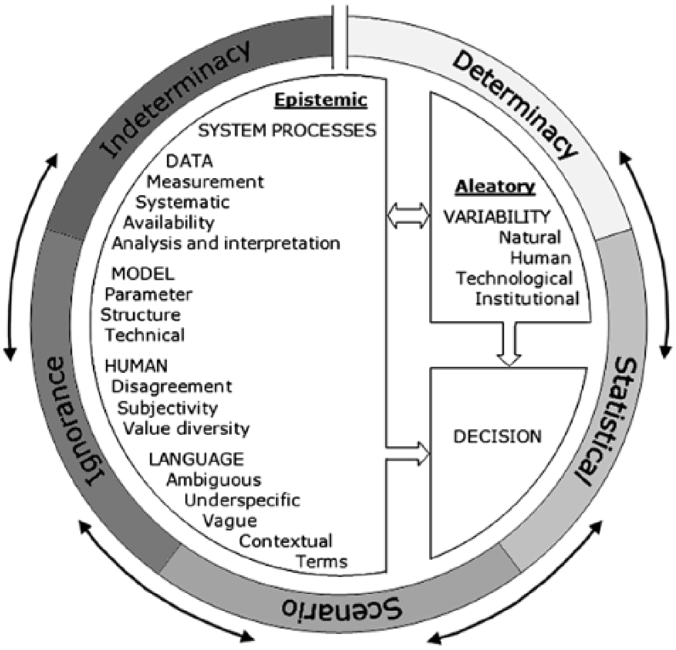


Figure 8. Skinner *et al.*'s uncertainty typology (source: Skinner *et al.*, 2014a; p214) [11]

3.4 Sources of uncertainty in environmental data science

3.4.1 Data

The increasing volume of data available, along with a focus on replicability, reproducibility and transparency, discussed in chapter 2, has focused attention on the sources and quality of data (Keller *et al.*, 2017). Many uncertainty studies have concentrated on uncertainties in models, with much less consideration of uncertainties in datasets (Zumwald *et al.*, 2020).

Maier *et al.* (2008) have considered where uncertainties can arise during data collection. Measurement uncertainties can be due to:

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- the type of instrument used (e.g. measurement precision)
- instrument calibration
- data recording method (e.g. manual or automatic)
- frequency of measurement and recording
- data transmission and storage
- type of data recorded
- missing data and reasons for this
- not all relevant data recorded (creating biased or incomplete results)
- length of data record which could impact the types of events captured.

Some of these could be described as errors and add to the confusion around the definition of uncertainty. Errors are described as either non-sampling or sampling. Non-sampling errors relate to the design, data collection and processing methods used. Sampling errors occur when the dataset is extrapolated and therefore not based on actual data collected (European Commission. Statistical Office of the European Union, 2019). In the past, the natural variability or aleatory uncertainty in data was thought to be due to mistakes (Lindley, 2014). The relationship between error and uncertainty is controversial. Henrion and Fischhoff (1986; p2) state that error and uncertainty "are used almost interchangeably" and are distinguished by defining the uncertainty as the assessment of the probability of an error. Smithson (1989) includes uncertainty as a feature of error, whereas Smets (1997) describes imprecision, inconsistency, and uncertainty as separate categories, including error under imprecision. More recently in a Eurostat document entitled 'Data uncertainties: their sources and consequences' (European Commission. Statistical Office of the European Union, 2019), errors are presented as the main source of uncertainty. However, Skinner *et al.* (2014b) conclude that although errors lead to a lack of accuracy in the data this represents only a small source of uncertainty in their typology. All the measurement problems, mentioned above, can affect availability, precision and/or accuracy of data (Skinner *et al.*, 2014b).

Many environmental data scientists do not collect their own data so rely on using secondary data. However, locating available data and gaining access to data can be problematic. This could be due to difficulty of locating data, because it is difficult to find.

Data may be inaccessible because a dataset is incomplete, or unusable due to measurement uncertainties, as mentioned above, or due to available data not being in a suitable format or to the scale required (Hox and Boeije, 2005). Satellites are an important source of environmental data, however, there are limitations, such as the time of day that the satellite passes a particular location of interest, the weather conditions at the time of passing, i.e. if there is cloud cover then data collection can be limited. Additionally, raw satellite data needs to be processed before it can be used (Edwards, 2010).

Irrespective of these problems there is a large volume of environmental data available and once data has been obtained and, if necessary, processed into a useable form, it can then be analysed. Analysis is the next step along the data-to-decision pathway where uncertainties can occur.

3.4.2 Data analysis methods

Increasing availability and capacity of computers have enabled an increasing sophistication of the different tools used for analysis of environmental data and phenomena over the years. Computer models are widely used within environmental research, so this subsection describes the various types of models that are used within the environmental context and uncertainties that arise from their use. The two main types of model used for environmental research are:

Process or Physical models: are used by environmental modellers to represent a natural system in order to understand the physical, chemical, and biological mechanisms and explain *what* is happening. Process-based models are useful for simulating complex systems, such as global climate changes.

Data-driven models: use mathematical equations applied to data to identify statistical relationships between observed data and environmental variables to predict the *probability* or likelihood of an event/s or environmental change/s occurring. They can be used to provide predictions even when the processes are not completely understood

(Knüsel *et al.*, 2020). These are also used for smaller scale environmental phenomena, such as air quality research.

Models can be combined into Integrated Assessment Models (IAM) to look at different environmental aspects (oceans, land, atmosphere), particularly to aid complex decisions, for example they are used by the global change research community (e.g. Rotmans and Van Asselt, 2001; Laniak *et al.*, 2013; Kirchner *et al.*, 2021). Kirchner *et al.* (2021) define them as "an interdisciplinary system of linked empirical datasets and mathematical models that are based on disciplinary theories". Integrated modelling can provide a more holistic view when stakeholder knowledge is incorporated (Dunford *et al.*, 2015). However, IAMs involve linking models so there are concerns about how uncertainties propagate through the chain (Bastin *et al.*, 2013).

All models can be used to provide different scenarios for decision-making. Different assumptions can be explored to provide possible alternatives for decision-making when there are many uncertainties. However, one problem with these models is deciding which "unknowable futures to study" (Dunford *et al.,* 2015).

Uncertainties within modelling processes have been studied by many authors (c.f. Oreskes *et al.*, 1994; Bastin *et al.*, 2013; Kirchner *et al.*, 2021). Oreskes *et al.*, (1994; p641) discuss the difficulties of verifying and validating models of natural systems as they are not 'closed systems', and "are laden with inferences and assumptions". Moreover, Doyle *et al.* (2019) conclude that often model results are communicated to decision-makers without details about assumptions made or clarification about other uncertainties, described as a 'black box'.

'Model uncertainty' is used to encompass all uncertainties associated with modelling, however, Doyle *et al.* (2019) state that this is often used synonymously with 'structural uncertainty' so they suggest that the encompassing term should be 'model related uncertainty'. Model related uncertainties appear at various stages of the modelling process, with the following described in modelling literature:

- Context (Walker *et al.*, 2003) provides the model boundaries of the system, also called model context (Warmink *et al.*, 2010), system boundaries, system resolution (Kirchner *et al.*, 2021).
- Model inputs (Walker *et al.*, 2003), or system data (e.g. the initial data used in the model) and driving forces (e.g. data for the driving forces of the model) (Kirchner *et al.*, 2021).
- Parameter uncertainty comes from the data and the methods used to calibrate the model parameters (Bedford and Cooke, 2001; Walker *et al.*, 2003).
- Structure, the mathematical formulation of the system, definitions, calculations, equations, algorithms (Walker *et al.*, 2003).
- Technical implementation, caused by flaws or bugs in the computer hardware or software (Walker *et al.*, 2003).
- Outcome uncertainty in the results due to the potential accumulated uncertainty (Walker *et al.*, 2003).
- Assumptions made and values of modeller (Kloprogge, 2011). Aspects of this type of uncertainty are discussed in the later chapters.

It is clear from this list that there are many uncertainties associated with models, leading to the often-quoted statistician, George Box "all models are wrong, but some are useful" (Box, 2023). Once uncertainties from data and models have been considered, the next step on the data-to-decision pathway are uncertainties arising from human subjectivity and judgement.

3.4.3 Behavioural and cognitive

Uncertainties due to human involvement in the environmental decision-making process are important but are difficult to handle as they are subjective and cannot be quantified (Ascough *et al.*, 2008). Uncertainties can arise from all stakeholders along the pathway, such as from behaviour, beliefs, values, misunderstanding due to language use or communication issues, as well as the level of uncertainty or even ignorance (as discussed earlier in section 3.2.3). Alongside these types of uncertainty, the psychology of judgement also impacts decision-making.

The incorporation of human behaviour into a decision system uses normative theory to consider the probability of a particular action, which relies on people acting in an expected way (Parsons, 2001). However, human behaviour can be unpredictable, such as a contradiction between what someone says and what they do (cognitive dissonance) creating the uncertainty of behavioural variability (van Asselt and Rotmans, 2002). For example, 'decision uncertainty' arises when results do not provide a clear decision path and future actions are unpredictable and unknowable (Ascough II *et al.*, 2008).

In group situations, 'disagreement uncertainty' can arise when individuals are unable to agree on methods, results, or conclusions (Morgan and Henrion, 1990). This could be further divided into 'paradigmatic uncertainty' caused by disagreement on the framing and methods used to solve a problem, and 'translational uncertainty' when there is disagreement on scientific findings, so no particular decision option is favoured (Kirchner *et al.*, 2021). These types of uncertainty can be affected by 'stakeholder uncertainty', when the views of a particular individual or group are perceived to be more important than others (Maier *et al.*, 2008), and by value diversity whereby people's perspectives and values affect their perception or definition of a problem, or the decision/s they make (van Asselt and Rotmans, 2002).

With all these different uncertainties, psychologists have proposed the controversial theory that people use other cues or heuristics to make judgements and decisions quickly when confronted with complex and uncertain problems (c.f. Gigerenzer and Gaissmaier, 2011). Gigerenzer and Gaissmaier (2011; p454) define a heuristic as "a strategy that ignores part of the information, with the goal of making decisions more quickly, frugally, and/or accurately than more complex methods". The concept of heuristics was first suggested in the 1950s by the economist and cognitive psychologist Herbert Simon, who suggested there were limitations to rational decision-making. However, in the 1970s, Kahneman and Tversky (1972) suggested that heuristic decisions create bias as they are not based on probability, they are therefore not objective and so are less accurate (Parsons, 2001). However, in situations of uncertainty where quantitative information is not available, heuristics provide a means of judging qualitative information to make a decision (Gigerenzer and Gaissmaier, 2011). This also resonates with the use of emotions and beliefs to make judgements, described as post-truth in chapter 2.

An additional behavioural uncertainty, discussed in chapter 2, is the use of uncertainty to create doubt, by using misleading information or messaging which misrepresents analyses (Oreskes, 2015). Biased information can be used to influence the decisions people make, similar to the aims of nudge theory that can be used to manage people's behaviour. By affecting a decision environment to influence the likelihood that individuals will choose one option over another, nudges have been used as an environmental policy instrument (Carlsson *et al.*, 2021). Although a key feature of nudge theory is that individuals maintain freedom of choice and perceive control of their decisions (Thaler and Sunstein, 2009), the nudges help to reduce uncertainty and aid decision-making. The use of Nudge Theory to improve public policy and services has gained momentum in the UK with the installation of the Government’s Behavioural Insight Team (BIT), or ‘Nudge Unit’ in 2010.

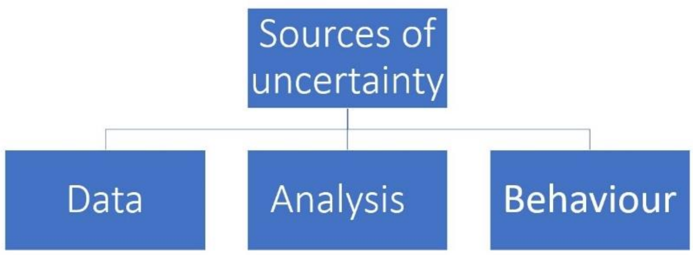

Figure 9. Summary of the sources of uncertainty described in section 3.4

Figure 9 provides a summary of the three main sources of uncertainty discussed in this section. Once these have been identified and assessed, options for handling the different uncertainties can be considered, so that the best information for making decisions is available.

3.5 Handling uncertainty for decisions

The different uncertainty sources have different impacts on and relevance to a decision. Many methods to assess, reduce, handle and/or manage uncertainty are available, and are also impacted by the level of the uncertainty. As the level of uncertainty increases towards ignorance, the available methods become increasingly qualitative. This section provides a brief synopsis rather than a comprehensive review of the many ways that uncertainty can be handled.

3.5.1 Quality control

Recognising the importance of quality management, Funtowicz and Ravetz (1990; p1) state: "[t]he issue of quality control in science, technology and decision-making is now appreciated as urgent and threatening". It is vital throughout the whole research process, enabling transparency and openness as discussed earlier in chapter 2, section 2.5.1. Quality control (QC) provides a means to reduce both sources and levels of uncertainty. For example, QC could pick up some data measurement errors or problems with an analysis, thereby potentially reducing a source of uncertainty. Additionally, by providing QC information the level of uncertainty of a decision-maker could be reduced. In the UK, the Government require any research analysis used for governmental decisions complies with a set of quality guidelines, known as the Aqua Book (Treasury, 2015). This document ensures that any analysis carried out is fit-for-purpose and that quality management follows best practice to ensure consistency of research used by government. It also includes advice for those who commission the research, including elements of co-design, thus providing quality guidelines that relate to the production of post-normal research. These guidelines advocate the importance of understanding and communicating uncertainty, preferably quantitively if possible or using qualitative terms if not, e.g. by estimating the likelihood of specific outcomes rather than a best estimate (similar to the IPCC terminology discussed in chapter 2). However, the amount of uncertainty analysis carried out needs to be proportionate to the decision to be made, the level of the uncertainties experienced and the resources available for the research.

A variety of initiatives to standardise and promote good practice, particularly due to the increased use of shared data, have been adopted. In the UK, the research community has developed a Concordat on Open Research Data (2016) setting out ten principles for using research data:

- Open access to research data is an enabler of high quality research, a facilitator of innovation and safeguards good research practice.
- There are sound reasons why the openness of research data may need to be restricted but any restrictions must be justified and justifiable.
- Open access to research data carries a significant cost, which should be respected by all parties.
- The right of the creators of research data to reasonable first use is recognised.
- Use of others' data should always conform to legal, ethical, and regulatory frameworks including appropriate acknowledgement.
- Good data management is fundamental to all stages of the research process and should be established at the outset.
- Data curation is vital to make data useful for others and for long-term preservation of data.
- Data supporting publications should be accessible by the publication date and should be in a citeable form.
- Support for the development of appropriate data skills is recognised as a responsibility for all stakeholders.
- Regular reviews of progress towards open research data should be undertaken.

Initiatives which incorporate the full research process have been developed to provide the research community with principles to ensure that their data science research follows best practice and is as robust as possible. These include:

FAIR: A group of stakeholders have developed the FAIR (Findability, Accessibility, Interoperability, and Reusability) principles for application in data management to ensure transparency, reproducibility, and reusability (Wilkinson *et al.*, 2016). Their aim is that alongside data FAIR should also apply to the algorithms, tools, and workflows that led to that data.

TRUST: Building on FAIR, Lin *et al.* (2020) have set out some guiding principles for using digital data repositories. These form TRUST (Transparency, Responsibility, User focus, Sustainability and Technology), again providing a framework to promote best practice for managing data.

RIGOUR: The UK Government guidance on producing quality analysis for government (Treasury, 2015) requests that the principles of RIGOUR (Repeatable, Independent, Grounded in reality, Objective, Uncertainty-managed, and Robust) are applied to any research that is used by Government departments to ensure that the key aspects of verification and validation are addressed.

FACT: which focuses on the scientific challenges of being, Fair, Accurate, Confidential, and Transparent (van der Aalst *et al.*, 2017).

CARE: these principles for the governance of indigenous data reflect the need to protect people's rights when sharing data. They cover Collective benefit, Authority to control, Responsibility and Ethics (Carroll *et al.*, 2020).

In addition to these, for data to be reusable by others, it needs to be accompanied by detailed metadata, defined as 'data about data' (Hey and Trefethen, 2003) or 'information about data' (Michener, 2006).[12] As the users are often distant from the producers (as per the uncertainty trough mentioned earlier) metadata is required to reduce ignorance and reduce the need for making assumptions. There are four types of metadata for scientific datasets (Saux, 2024):

[12] For more details see: What is metadata and why is it as important as the data itself?

- Descriptive metadata – provides details and context of the dataset, i.e. the provenance – Who, What, Where, When and How. This includes how the data was produced (e.g. fieldwork processes, instrumentation, sampling protocols) how it has been processed and the quality control processes that have been applied.
- Structural metadata – describes the format of the data and how it is organised.
- Relationship metadata – provides details of links to other data, along with version control.
- Administrative metadata – provides information on licencing, how it was funded and how the data can be used.

Metadata keywords aid the findability of datasets available for reuse using online searches. Metadata can also be used to judge the quality of the dataset and enables a user to decide whether datasets can be integrated with others, i.e. the interoperability. In the 1990's it was recognised that information about data was not consistent, leading to the development of various 'standards' which also provided a means to judge different aspects of data quality. These included ISO19115/19157 for geospatial data and ISO 15836 for more general metadata standards, which are not domain specific, known as Dublin Core. [13] Brodeur *et al.* (2019) provide a detailed review of the development, evolution and an overview of geographic metadata standards. ISO 19157 focusses on the quality of geographic data which are described using six quantitative features – completeness, logical consistency, positional accuracy, temporal accuracy, thematic accuracy, and usability. The data quality is then assessed using two main measures – counting and uncertainty – with counting based on counting errors and uncertainty based on using statistical methods to model the error of measurements (Brodeur *et al.,* 2019). The assessment of data quality is therefore focussed on quantitative measures of errors in the data without other aspects of data quality considered. Importantly, details about the provenance or lineage are not included.

[13] ISO15836: is the standard for maintaining quality of metadata. Known as the 'Dublin Core', it features 15 elements for description of metadata (c.f. https://en.wikipedia.org/wiki/Dublin_Core)

Provenance describes how the data came into existence and the stages it has passed through before becoming available for reuse. Standards for data are, however, constantly evolving. For example, a recent development is the incorporation of vocabularies to encourage consistent terminology to aid discoverability of datasets (Brodeur *et al.*, 2019).

Metadata provides an indication of data quality; however, the quality of the metadata also needs to be assessed. A review by Kumar, Chandrappa and Harinarayana (2024) found that the commonly used dimensions for assessing metadata quality are completeness, accuracy, consistency, accessibility, conformance, provenance, and timeliness. However, they also note that there is no consensus on the exact definition and measurement of these. Quality control of the datasets held in data repositories is judged by the availability and quality of metadata. For example, the EIDC requires data deposited to conform to the UK Gemini Metadata standard based on ISO19115/19157.

Implementation of guiding principles and metadata standards as described above aim to homogenise research, leading to improvements in the quality of data, metadata and methods to reduce some avenues of uncertainty. However, uncertainties in research still need to be handled and assessed, some methods have been used for many years and others are becoming more widely utilised.

3.5.2 Traditional methods of handling uncertainty

Statistical uncertainty is generally the main understanding of 'uncertainty' in the natural sciences and covers any uncertainty that can be described quantitatively (Walker *et al.*, 2003). Keller *et al.* (2016; p97) assert that "[s]tatistics clearly deserves its title as the science of uncertainty, especially in the field of data quality". Lindley (2014) narrows this further to defining uncertainty as probability.

Probability theory is the most widely used technique for quantifying uncertainty (Morgan, Henrion and Small, 1990). Probability theory provides a sampling distribution from which confidence intervals can be derived to represent the uncertainty in a data sample (Spiegelhalter, 2020). However, the method used varies depending on whether a statistician follows a classic (or frequentist) or Bayesian approach to statistics. The frequentist statistician considers probability that relates to aleatory uncertainty and the frequency of random events. These methods are less suitable for environmental problems (Aguirre *et al.*, 2013) leading to the increasing use of Bayesian methods for environmental research (Gelman and Shalizi, 2013). As this is a relatively contemporary development, Bayesian methods are discussed in the following subsection.

Decision theory aims to make the best decision possible using available information, derived using probability. One type of decision theory is an Optimal Choice Framework (OCF) which uses a probability-based approach to determine the best response. In January 2017, the UK research councils provided two years of funding for two networks, Challenging Radical Uncertainty in Science, Society and the Environment (CRUISSE) and Models to Decision (M2D) to report on the state of current research into real-world decision-making under uncertainty and propose a future research agenda. Consisting of academics and policymakers with a wide range of backgrounds in physical, mathematical, social, political and psychological science, the CRUISSE group concluded that the majority of decisions are based around an OCF (CRUISSE, 2017). OCF frameworks are used in many disciplines to answer a variety of problems or explore possible options, however their use becomes limited when it is not possible to quantify information and there are gaps in knowledge (Polasky *et al.*, 2011).

As probability cannot be used for all uncertainties, other theories which incorporate qualitative elements have been developed, although still based within mathematics, These include fuzzy set theory (Zadeh, 1965; cited in Beven, 2010) and possibility theory, which incorporate incomplete knowledge into the variability measured by probability theory to provide a quantified possible outcome (Dubois, 2006). Similarly, evidence theory (also known as Dempster–Shafer theory or reasoning under uncertainty) is based on possibility and imprecise probability theories. First introduced by Arthur P. Dempster, the theory was developed by Glenn Shafer into a mathematical theory of evidence. The theory allows the combination of all the available evidence from different sources to arrive at a degree of belief, represented by a mathematical object called a belief function (c.f. Parsons, 2001).

Alongside these traditional methods to assess and handle uncertainty for decision-making, the increasing use of computer models to analyse and simulate environmental challenges has enabled the advancement of methods for evaluating uncertainty. These methods are discussed in more detail in the following section.

3.5.3 Contemporary methods of uncertainty assessment

Increasing computing power has led to the development and use of increasingly complex computer models in environmental research. This has enabled an increase in repetitions and complex computations to be carried out to simulate alternative scenarios to aid decision-making. However, as discussed in section 3.4.2 there are many sources of uncertainty associated with computer models. Two standard methods used to ascertain uncertainties are *uncertainty analysis* and *sensitivity analysis*. Uncertainty analysis focuses on the uncertainty of the output; sensitivity analysis looks to quantify the contribution of the input parameters and assumptions to the output/uncertainty analysis (Saltelli *et al.*, 2019). Jakeman *et al.* (2006; p602) promote best practice for uncertainty analysis stating "[g]ood practice increases the credibility and impact of the information and insight that modelling aims to generate", although Saltelli *et al.* (2019) conclude that many sensitivity analyses are of poor quality and the terms for the two methods are often used synonymously. However, these methods provide an indication of the quality of the model and its outputs to aid a decision-maker. Model emulators are a developing research area, providing simplified versions of complex models. These are used to provide quicker, albeit less robust, outputs and they can be used to carry out sensitivity analyses of sophisticated models (c.f. Ratto *et al.*, 2012).

Highlighted earlier, the increasing use of Bayesian methods for statistical analyses of environmental problems represents a changing philosophy in statistics. These methods incorporate judgement, so they are more subjective and the Bayesian statistician can include assumptions, or 'priors', based on their experience. If new evidence becomes available applying Bayes' Theorem allows revision of the original prior beliefs, producing 'posterior' beliefs (Spiegelhalter, 2020). This incorporation of new information also provides a means of reducing uncertainty. Bayesian methods and the associated philosophy are investigated from a statistician's perspective in chapter 6.

3.6 Conclusion

This chapter has examined a wide range of literature on uncertainty. Its primary objective was to provide a snapshot of the various uncertainties relevant to environmental data science and explore methods for assessing, mitigating, or managing these uncertainties to establish robust evidence for informed decision-making.

The key findings from this literature review are:

Diverse perspectives on uncertainty. Uncertainty is a concept that differs across disciplines, leading to multiple interpretations and meanings. This ranges from authors who focus on uncertainty as a statistical concept and others who prefer a more qualitative definition.

Relevance of environmental risk management literature. The most pertinent literature for environmental data science is found in the field of environmental risk management, which uses environmental data to establish the risks for environmental decisions. A widely cited typology of uncertainty from this domain is by Walker *et al.* (2003) who classify uncertainty into the categories of nature, location (source), and level.

Sources of uncertainty affecting environmental data science. Uncertainty relating to environmental data science research arises from three primary sources: data, analysis, and human behaviour. The latter incorporating decisions about the research methods, collaborations and communication. Inclusion and expansion of these provide the basis for a data-to-decision uncertainty pathway (see blue arrowed pathway on Figure 10).

Analysis techniques for handling and reducing uncertainty. To manage data uncertainty various analytical methods are employed based on statistical and modelling techniques. Fundamental to these are quality assessment procedures, which follow a variety of established and new guidelines and standards.

These findings inform the development of a new typology of uncertainty relevant for environmental data science. The diverse perspectives indicate that different stakeholders along the pathway from data to decision will have different priorities and interpretations of the different elements. The environmental risk literature provides a basis for the typology, by aiding understanding of the types and sources of uncertainty that relate to environmental challenges. This understanding, alongside consideration of techniques to explore and handle uncertainty, divide uncertainty for environmental data science into four distinct categories (see Figure 10), described in more detail below.

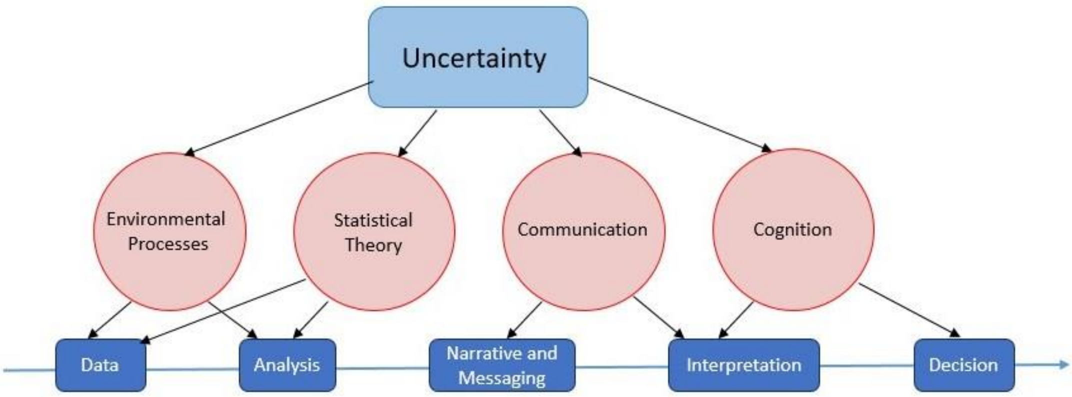

Figure 10. Summary of the sources of uncertainty in environmental data science and their influence on the data-to-decision pathway

Uncertainties associated with data and any analysis relevant to environmental process modelling are incorporated into a section called **Environmental Processes**. These uncertainties are experienced when researchers are trying to understand ***what*** is happening in the environment (also informed by literature from chapter 2).

Data uncertainties are included again, along with statistical analysis methods into a **Statistical Theory** section. This covers uncertainties associated with the quantitative assessment of uncertainty and therefore provides the ***probability*** of an event or environmental change occurring. Uncertainties due to natural variability, often called aleatory uncertainties, would also come under this category.

Although **Communication** was included in the Introduction it has not been mentioned as a separate section in this chapter. It is an inherent part of research when used to make decisions, so moved to be a distinct category in Figure 10. This section therefore includes all uncertainties which occur due to communication, including language uncertainties, such as ambiguities, when different environmental disciplines are combined. It also includes uncertainties created by the way the research is presented and the message it portrays. This narrative or message can affect a stakeholder response and interpretation of scientific evidence being presented, and therefore overlaps with cognitive uncertainties. On the data-to-decision pathway, behavioural uncertainties have been split into those created by the way information is presented and those by the way it is interpreted.

The **Cognition** section includes the behavioural uncertainties discussed, as well as the level of uncertainty**.** It covers the researchers' confidence in their work, as well as the understanding and values of the decision-makers, alongside the level of risk from making, or not making, a decision.

The first two categories cover the quantitative uncertainties that occur within data and analysis methods. The second two categories incorporate the qualitative uncertainties that can eventually affect a decision. These latter two categories – communication and cognition – also relate to uncertainties arising from data and analysis but remain distinct to show their importance when providing policy-relevant scientific evidence. The acknowledgement of the uncertainties arising from these categories is also a major difference between normal and post-normal science.

This new typology promises to be a valuable tool for environmental data scientists and decision-makers as they navigate the complexities of uncertainty in their efforts to address environmental challenges.

The typology will be further developed in chapter 8, incorporating insights from interviews and focus groups discussed in subsequent chapters. The following chapter describes the methodology and methods used for this data collection.

4 Research Methodology and Methods

4.1 Introduction

This chapter describes the methods used to achieve the aims and objectives set out in the introductory chapter. To broaden the literature review in the previous two chapters by incorporation of lived experiences data was collected from three different research studies. These explored perspectives of different stakeholders on uncertainty and decision-making when researching environmental challenges. The studies were: an interview study with scientists and decision experts involved with the challenge of ozone depletion to provide insights for a historical case study, an interview study with application-orientated environmental data scientists (CEEDS), and a focus group study with method-orientated data scientists (DSNE). Research methodologies and their underlying philosophies play an important role in cross disciplinary research. Investigation of these philosophies provides an explanation of the methodology behind this multidisciplinary study, as well as providing a background to understanding the different perspectives of stakeholders affected by environmental problems.

Figure 11 shows the overall design of the study, and the outcomes from the three amalgamated research studies. A multidisciplinary literature review was undertaken to understand the different definitions of uncertainty, how uncertainty within science has changed, environmental science and decision-making, and to review the current literature on environmental data science. This review provided a basis for conducting the three aforementioned research studies to capture the rich, personal experiences of the participants. Each of the studies considered different elements of uncertainty that can occur from the collection of data to its use for decision-making. These complementary studies were used to build up a picture of contemporary environmental scientific research, and how environmental data science can be incorporated to support robust decision-making.

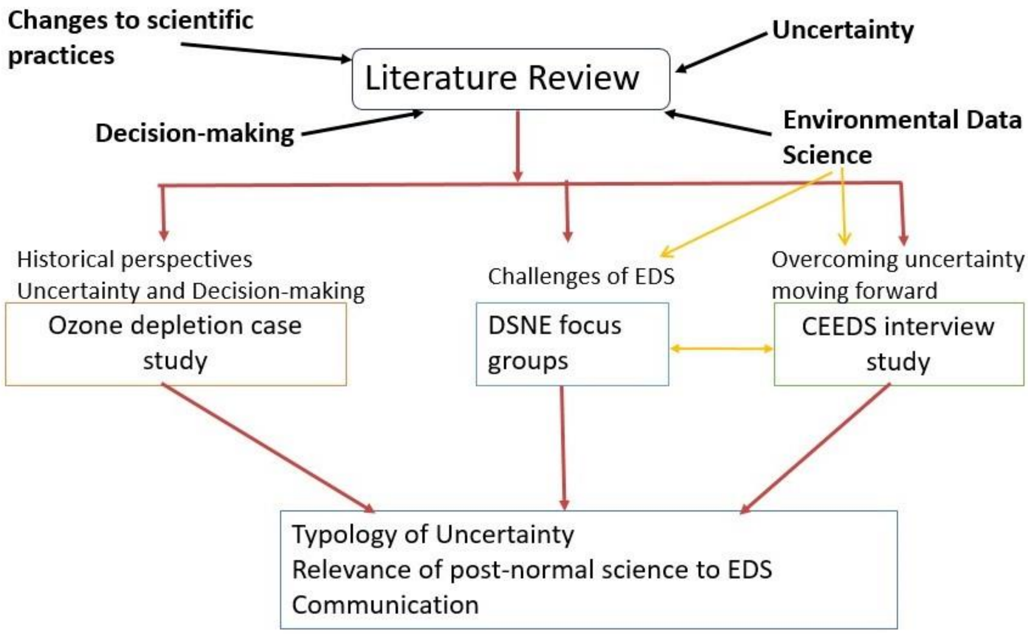

Figure 11. Summary diagram to provide an overview of the study

The chapter provides further details of the research design (4.3), the data collection methods, and the analysis methods used (4.4). As this study applies qualitative methods to understand (mainly) quantitative research, this chapter starts by considering the different types of philosophical reasoning that underpin quantitative and qualitative research (4.2).

4.2 Background to methodology

Different research methodologies and philosophies underpin different types of research. These influence individual beliefs, perceptions and understanding, affecting the way that evidence provided for decisions is created and is interpreted and/or trusted. It is not within the scope of this thesis to delve into this too deeply, but it is included because research methodology and personal philosophy impact on aspects of research collaborations and therefore on environmental data science practices.

These different philosophies introduce two main types of reasoning approaches – inductive and deductive. The deductive approach is used by researchers whose research is based upon a pre-determined theory or hypothesis (usually used in natural sciences), whereas the inductive researcher collects data first and then bases their conclusion or theory on these (usually used in social sciences). However, although these are generally used by two distinct philosophies of science – positivist (deductive)/interpretivist (inductive) – there can be some overlap between them (Moses and Knutsen, 2019). In addition to these is abductive reasoning, which combines elements of the two (see Figure 12). Like induction it starts with data, which is then used to define a hypothesis, which is then tested – so this approach uses available information to produce a conclusion that provides a best estimate based on incomplete information (Harman, 1965 cited in Miller, 2019).

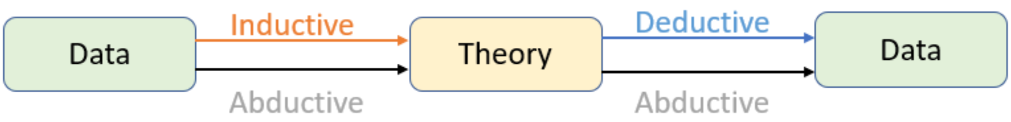

Figure 12. Inductive, deductive, and abductive reasoning

These types of reasoning are used by the three different strands of philosophy of science, also known as metaphysics (Moses and Knutsen, 2019), summarised in Table 4.

Table 4. Summary of the three strands to philosophy of science

	Ontology	**Epistemology**	**Methodology**
	Study of Being	Study of Knowledge	Acquisition of Knowledge
Reasoning (deductive) in natural sciences	Objectivism or Realism	Positivism	Naturalism
	Belief that can find absolute 'truth' or reality		
Reasoning (inductive) in social sciences	Relativism	Interpretivism	Constructivism
	Belief that there are many realities depending on the researcher		
Overlapping reasoning	Critical realism	Pluralism	Contextualism
	Belief that there is a 'truth' but that there may be different versions of 'truth'		

Ontology (the study of being) and epistemology (the study of knowledge) appeared in chapter 3 while discussing the types of uncertainty, with aleatory uncertainty relating to ontology[14] and epistemic to knowledge creation. The third strand is methodology and considers how knowledge is acquired. Within these strands, differing belief positions are seen:

Objectivism/realism (ontological) / Positivism (epistemological) / Naturalism (methodological): this type of reasoning comes from the natural sciences and is the belief that there is an absolute truth or reality to be sought, a 'Real World'. The researcher starts with a pre-defined hypothesis, collects data, interprets it deductively to provide an objective conclusion provided by the data with no influence from the researchers' values. It is also known as empiricism and is associated with quantitative data analysis methods (c.f. Bryman, 2016; Moses and Knutsen, 2019).

Relativism (ontological) / Interpretivism (epistemological) / Constructivism (methodological): this type of reasoning comes from the social sciences and is the belief that there are many realities and acknowledges that the researcher has a role in constructing these. The researcher collects data and interprets it inductively to develop their theories. Therefore, the research outcomes are subjective and generally associated with qualitative data analysis methods (c.f. Bryman, 2016; Moses and Knutsen, 2019).

An additional development is a recognition that there are scientists who overlap between the two philosophical positions above. First described as 'critical realism' by Bhaskar in 1975, who suggested that there is a truth to be found, but that there could be reasons why this might not actually be possible:

> *"The sort of ontology I was arguing for was the kind of ontology in which the world was seen as structured, differentiated and changing. And science was*

[14] and sometimes referred to as this – see Table 1 in chapter 3.

> *seen as a process in motion attempting to capture even deeper and more basic strata of a reality at any moment of time unknown to us and perhaps not even empirically manifest" (cited in Moses and Knutsen, 2012; p303)*

This is also called 'pragmatic realism' (Beven, 2010) or 'scientific realism' (Moses and Knudsen, 2019). Moses and Knudsen (2019) suggest that although fundamentally realist, some scientists recognise that finding the truth of the Real World is complex and that inductive reasoning may be necessary in some instances. Beven (2010) recognises that models used to predict environmental changes are open systems and that, in reality, it is not known exactly how parameters act or interact. This philosophy still retains the realist mind-set but allows the researcher to be pragmatic about the difficulties of achieving 'reality'. It is a particularly relevant philosophy for studying complex environmental problems beset with uncertainties. The cross-disciplinary nature of environmental research, each with its different ontology and epistemology creating a source of tension, requires the scientists engaging with this type of research to be critical realists, and embrace epistemological pluralism (Ainscough, Wilson and Kenter, 2018). Funtowicz and Ravetz (1994) state that the philosophy of post-normal science falls into a diversity of ontologies which they call emergent complex systems. This is based on changes in attitude and direction at the time of concept development and led to the growth in the appreciation of complex systems.

The research questions that underpin this thesis involve understanding people's experiences and perspectives. Therefore, the methodology used for this research uses an inductive approach to develop concepts from the data obtained from the interviews and focus groups.

4.3 Research design

The research design aims to produce trustworthy research using rigorous and methodical qualitative methods (Attride-Stirling, 2001), with provision of clear details about the methods used and the assumptions made (Nowell *et al.*, 2017). Interviews and focus groups were held to explore the views, thoughts and practices of data scientists, environmental data scientists, environmental scientists and those involved with environmental decision-making. Surveys or questionnaires could have been used but interviews allowed for discussion and further exploration of any points raised. The analysis of the data collected follows a contextualist approach to provide an interpretation of what people say and considers that there is no absolute truth but that several different realities can co-exist because people perceive reality differently from each other (Braun and Clarke, 2013). The following sections describe the cross-cutting design methods used for all three research studies.

4.3.1 Interviews and focus groups

Interviews and focus groups were chosen to gain information about people's understanding of their experiences – '*the world of beliefs and meanings'* (Arksey and Knight, 1999; p15). These methods provide an in-depth exploration of participants perspectives, actions and practices, and enable interaction so that the interviewer can gain an in-depth understanding of motivations and reasons for particular behaviours. The combination of responses from several people enables understanding of norms/standard practices within a specific domain.

Semi-structured interviews provided one of the main sources of data collection for this project. It was not necessary to ask standard questions to each participant, so semi-structured questions provided areas of interest to pursue but allowed flexibility and the opportunity to go into further depth if the interviewee mentioned interesting nuances of their research area. Two interview studies were undertaken. One for the stratospheric ozone depletion case study (n=6) with atmospheric scientists and those involved in the decision process to explore uncertainties and decisions from a historical perspective, along with the experiences of the scientists' when working at the science-policy boundary. The other with members of the Centre of Excellence in Environmental Data Science (CEEDS) (n=13) a group of environmental data scientists from different environmental sub-disciplines to gain a deeper insight into the uncertainties that they experience and any mitigating techniques they employ. In addition to these, the opportunity arose to conduct two extra interviews with environmental scientists, which provided more in-depth insights into data collection and decision-making. The indicative questions for all interviews are included in Appendix E.

In addition to the semi-structured interviews, data was also collected from conducting three focus groups consisting of four or five members of the Data Science of the Natural Environment (DSNE) project (total n=13) designed to understand statistical uncertainty. Focus groups are defined by Morgan (1996; p130) as “a research technique that collects data through group interaction on a topic determined by the researcher”. Therefore, focus groups, rather than individual interviews, were more relevant for this part of the study to encourage a more discursive interaction between experts with a similar disciplinary background. This enabled observation of how individuals discussed uncertainty and statistics between themselves, and the sharing of environmental data science experiences. It was anticipated that these discussions would provide more in-depth insights than individual interviews, as the groups would use their practice language when conversing with peers (Landström *et al.* (2015).

4.3.2 Sampling

The participants for both the interviews and focus groups were purposively selected, as they needed to be working/have worked within the areas of environmental science or environmental data science. In addition to this, there are elements of convenience, with participants selected from the research organisations that the student is affiliated to, or people already known to the student. Convenience sampling has been criticised for being a less rigorous and justifiable method (Sandelowski, 1995 cited in Braun and Clarke, 2013). However, as environmental data science is a relatively new academic discipline[15] (Gibert *et al.*, 2018; Blair et al., 2019) the pool of environmental data scientists is not large, so it was felt that the groups selected provide a representative sample of experts working in this research area.

[15] The Journal ‘Environmental Data Science’ was first published in April 2022.

No sensitive data, such as demographic information, was collected as it was not relevant for the aims of this study.

4.3.3 Data analysis

Analysis of the data collected followed a thematic analysis approach, first mentioned by Boyatzis (1998) and developed and formalised by Braun and Clarke (2006, 2012, 2019).[16] Thematic analysis is a less philosophically rigid approach involving the 'generation' of themes following the coding of the qualitative data (Braun and Clarke, 2019). Thematic analysis enables the development of the themes inductively, without the boundaries of a pre-determined framework. Due to its popularity, Braun and Clark (2019) have reflected on their original paper (Braun and Clarke, 2006) suggesting that the method offers a very flexible methodological approach, but it requires reflection and transparency by the researcher about the assumptions they have made.

Once collected and transcribed the data was 'coded'. In the context of qualitative research 'coding' is the process of picking out words or short phrases that appear relevant to the study from language-based or visual data, and attaching labels or codes, so they can be linked into themes (Saldaña, 2013). Coding provides a "critical link" between the collected data and the analysis of its meaning (Charmaz, 2000). According to Saldaña (2013), several cycles of coding should be performed, to group, consolidate or add additional codes. Using the divisions of coding defined by Braun and Clarke (2013) this study undertook 'complete coding' whereby anything of interest was coded using the interviewees own words, known as in-vivo coding (Saldaña, 2013) or 'data-derived' (Braun and Clarke, 2013). This method of coding was chosen because the purpose of the interview data was to inform the research and lead to a holistic understanding of the experiences discussed by the participants.

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[16] Many qualitative studies use grounded theory (Glaser and Strauss, 1967), however, this approach is seen more as a methodology rather than an analysis method, following a positivist stance suggesting that themes appear objectively from the data (Charmaz, 2014). However, Charmaz suggested reforms to grounded theory that incorporated a constructionist version (Charmaz, 2000)

In thematic analysis the coded text is then collated into 'themes'. Themes are developed by the researcher from what they perceive to be the relevant recurring features mentioned by the participants (King, 2012). Three points to note when developing themes in thematic analysis are highlighted by King (2012):

1. A code needs to be repeated through the data to be developed into a theme. A single isolated example should not become a theme and therefore avoiding what Bryman (1988) has referred to as 'anecdotalism' (cited by Braun and Clark, 2006).
2. Themes are not objective and are influenced by the researchers' analysis.
3. Themes must be relatively distinct from each other.

The themes developed from the codes can be either 'data-driven' (inductive) or 'theory-driven' (deductive) (Kiger and Varpio, 2020). In the former, the themes are developed directly from the data, whereas in the latter the coding is based on a framework, such as with template analysis, which accepts that the researcher is approaching the data with specific questions in mind (Braun and Clarke, 2019). Since this thesis presents an inductive study the codes were derived from the data.

One advantage of thematic analysis is its flexibility to develop themes from the data. However, Bazeley (2012) states that a researcher needs to explain why the highlighted themes are important, and how they relate to each other, arguing that it is not sufficient just to state what the themes are.

Braun and Clark (2006) suggest the six phases for conducting thematic analysis are:

1. Becoming familiar with the data
2. Generating initial codes
3. Developing themes
4. Reviewing themes
5. Defining and naming themes
6. Producing the report

The following diagram provides a summary of the research design used for this study, showing Braun and Clark's (2006) six thematic analysis phases, and the iterative nature of this approach. It also incorporates an additional phase to allow for researcher reflection on their influence and assumptions, as mentioned above (Braun and Clarke, 2019).

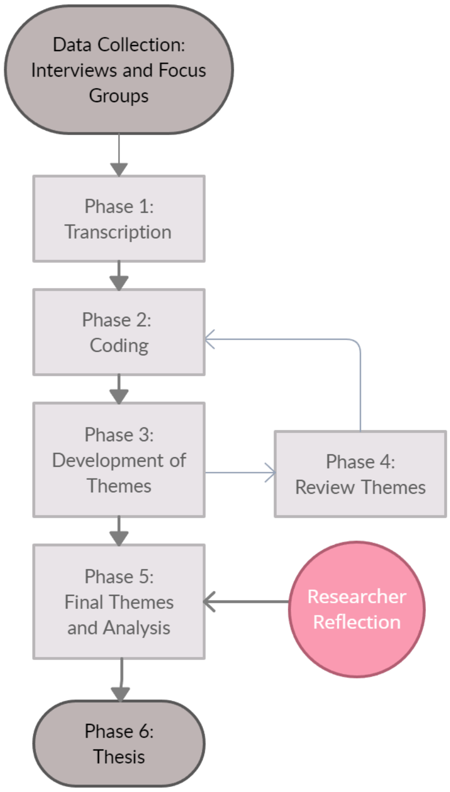

Figure 13. Summary diagram to show the research design of this thesis. It incorporates the six phases of thematic analysis described by Braun and Clark (2006) along with researcher reflection (Braun and Clarke, 2019)

4.3.4 Researcher positionality

The researcher is part of the Data Science of the Natural Environment (DSNE) project based in the Maths and Stats Department at Lancaster University, and therefore surrounded by environmental and statistical discussions, along with seminars and meetings. The researcher is also a member of CEEDS but had not met many of the interviewees in the CEEDS part of the study prior to the interviews.

Additionally, previous work experiences have also influenced this thesis. The ozone depletion case study was chosen to draw on personal experience. Between 1992 and

1996, the author provided administrative support to the European Ozone Research Coordinating Unit which was set up to coordinate research into stratospheric ozone depletion in Europe. At that time the Unit consisted of three scientists, John Pyle, Neil Harris and Joe Farman, along with an administrator. This employment provided access to experts who have been involved in this research area over a long period of time to draw on their experiences. Moreover, after this employment the author worked as an administrator for several science and technology studies (STS) orientated research centres, based at Lancaster University. These experiences are likely to have skewed the author's perception of scientific research at the policy interface, leading to an assumption that this is a common (and comfortable) situation for scientists. In a survey of global legislative experts Akerlof *et al.* (2022) found that 79.2% thought that scientists should work closely with decision-makers to incorporate scientific results into policy decisions, i.e. there is an expectation that scientists should provide policy-relevant evidence when required to.

Coming from a science-based background provides a realist background, so to then undertake a qualitative study the author wrestled with the ontology and epistemology of this research. On reflection, the study provides a critical realist approach. Due to this realist interpretation of the data, and inexperience and lack of confidence with qualitative research, the initial themes came directly from the interviewee's words, influencing Phase 3 of the research design. However, as familiarity with the data developed, other themes became more apparent, increasing the richness of the research and the confidence of the author.

4.4 Research methods

A multidisciplinary literature review was undertaken, starting with a wide-ranging exploration of uncertainty, narrowing to consideration of uncertainty within a scientific context. Data collection and the literature review ran concurrently, with interviews starting relatively early in the study. The interviews explored the types of uncertainty experienced by environmental data scientists and investigated the impact of these uncertainties on their working practices and the evidence that they produce for decision-making. The research studies are described in more detail in the following subsections, along with more in-depth details about ethics, transcription, coding, and data analysis techniques used for each study.

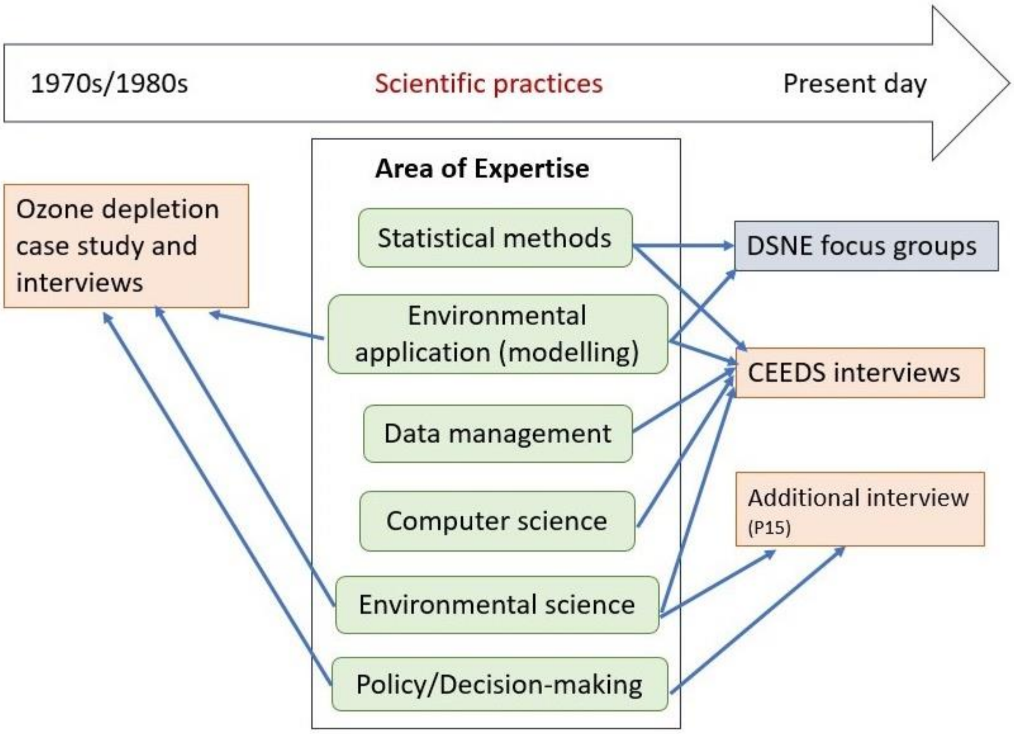

Figure 14. Diagram to show how the different studies relate to each other and the different areas of participant expertise feeding into each study

Figure 14 shows how the studies relate based on the expertise of the participants and the longitudinal aspect of the research. This breadth of expertise provided knowledge and perspectives from a variety of stakeholders to provide insights which can be used to take forward the use of data-driven evidence for environmental decision-making. The longitudinal aspect of the figure shows how the studies contribute to the discussion on changing scientific practices over the past 50 years. These range from the experts resolving the challenge of ozone depletion, to those currently involved in contemporary environmental data science. This figure highlights how the three different studies complement each other due to the experience of the participants, and the areas of expertise that have provided information on the different aspects of uncertainty incorporated into the typology in chapter 8.

4.4.1 Data collection

Ethics

Before the interviews and focus groups could be conducted, ethics clearance from the Lancaster University Faculty of Science and Technology Ethics Committee was sought (the application documents can be found in Appendix A). This was initially to carry out interviews and permission was granted in December 2019, followed by an amendment to include focus groups, granted in June 2021. All interview participants were provided with an information sheet about the study and requested to sign a consent form. As it was not felt that the subject area is particularly sensitive, interview participants were given the option to be named or remain anonymous. However, for the focus groups this option was not included on the consent form, as it was their membership of DSNE which provided their expertise, so all participants remain anonymous. Recordings of the interviews and focus groups were deleted once transcribed and checked. The transcripts remain as electronic files and are stored on the University's One Drive.

Stratospheric ozone case study

At the time of the author's employment, mentioned earlier, this was a rapidly expanding research area to understand the stratospheric chemistry and processes that led to the formation of the Antarctic ozone hole, reported in 1985. A worldwide agreement, the Montreal Protocol, to limit the use of the chloroflurocarbons leading to this loss of ozone, has been hailed as a success story for decision-makers (Solomon *et al*, 2020). It was felt that this topic and experience would make an excellent case study to look back at differences in how uncertainty was discussed and managed in the past.

This case study incorporates a literature review alongside interviews conducted with experts involved with this study area, some for over fifty years. Initially this study was to form the first data collection part of the thesis. However, due to Covid, this ran on longer and alongside other studies. The semi-structured interviews were conducted between December 2019 and March 2021, either in person or via Microsoft Teams or Zoom and were recorded. As mentioned above, the ethics consent allowed for participants to decide whether they could be named or remain anonymous. The ability to name participants added credibility to this particular research study, as it enabled information about their expertise to be included. Table 5 provides details for the interview group. These six experts, along with my own experience and knowledge, provided a rich selection of recurring themes which provided sufficient data for this case study. Further details about the individual expertise of the interview participants are provided in chapter 5, along with the resulting thematic analysis of these interviews.

Table 5. Interview Participants – Ozone depletion case study

Interviewee	Interview Date	Specialism
John Pyle	12.12.19	Atmospheric scientist & policy advisor
Oliver Wild	17.03.20	Atmospheric process modeller
Paul Young	06.04.20	Climate scientist
Neil Harris	22.04.20	Atmospheric scientist & policy advisor
David Warrilow	02.10.20	Senior government science advisor (retired)
Anon	17.03.21	Atmospheric chemist

CEEDS interview study

To understand environmental data science in practice and the challenges experienced by researchers in this domain semi-structured interviews were carried out between April and July 2020 with members of the Centre of Excellence in Environmental Data Science (CEEDS). CEEDS is a joint venture between Lancaster University and the UK Centre of Ecology and Hydrology. The aim is to create a community to tackle current environmental challenges by drawing on the experience of academics from many different environmental sub-disciplines, as well as computer scientists and statisticians, who are motivated by the application of data science methods to environmental problems.

The fifteen theme leaders were invited by email to take part in the study. Of these, thirteen agreed to participate in the study. Table 6 shows the date of interview and an indication of their broad specialism.

Table 6. Interview Participants – CEEDS

Interviewee	Interview Date	Specialism
P1	28.04.20	Environmental Scientist
P2	01.05.20	Environmental Scientist
P3	04.05.20	Data Management
P4	05.05.20	Statistician
P5	15.05.20	Statistician
P6	18.05.20	Computer Scientist
P7	22.05.20	Environmental Scientist
P8	29.05.20	Environmental Scientist
P9	01.06.20	Environmental Modeller
P10	09.06.20	Environmental Scientist
P11	08.07.20	Environmental Scientist
P12	13.07.20	Data Management
P13	23.07.20	Environmental Modeller
P14	04.11.21	Data Handler
P15	09.03.22	Senior Scientist/Policy Adviser

These interviews were carried out during the Covid pandemic lockdown by the author together with Lauren Thornton (another PhD student). This provided the author with an opportunity to observe a more experienced interviewer and therefore gain more confidence as an interviewer. Additionally, as the group of participants were of interest to both our studies it was more time effective for the interviewees to just take part in one interview session. Although there were some overlap of areas of interest, we had our own set of questions (see Appendix E), although it should be acknowledged that each other's questions would have influenced the resulting themes to some extent. We also had separate ethics consent, and differing consent forms (Lauren's gave everyone anonymity). Although the consent form for this study gave the option for participants to be named, the majority preferred to be anonymous, so in order to maintain consistency, all participants in the study remain anonymous and will be referenced in chapter 7 as shown in Table 6 (P1-P15).

The interviews were conducted using either Microsoft Teams or Zoom, depending on the preference or access of the interviewee, and lasted between 30 to 60 minutes. They were recorded using the inbuilt software of the online platform, and transcription of the interviews was divided between the interviewers. The transcripts were then coded individually to collect preliminary codes as the interviews were carried out, allowing incorporation into later interviews any additional lines of inquiry emerging from the earlier interviews. Following this, both researchers met virtually to discuss the full set of codes they had accrued and the initial categories they had organised these codes into. However, as described in chapter 7, the results and analysis presented in this thesis are derived from the authors individual examination of the data.

Following these CEEDS interviews, two further interviews were conducted by the author. One with a CEEDS member who was mentioned by P3 as example of someone who writes papers describing collection of data, to gain a more in-depth understanding of their day-to-day work. Additionally, the opportunity arose to conduct an interview with someone who works in an environmental policy advisor role (not a member of CEEDS). As both their thoughts will be included in chapter 7 with the CEEDS interviews they are added into Table 6 above as P14 and P15 respectively.

Focus group study

Recognising that a different perspective of uncertainty typically considered by statisticians was not sufficiently explored in the CEEDS interviews, a focus group study was designed to utilise the accessibility of members of the Data Science of the Natural Environment (DSNE) project, based at Lancaster University. This is a statistical methods-driven project to look at the challenges of ice sheet melt, air quality and land use.

An invitation to participate was sent by email to the DSNE mailing list (31 people) and people were asked to sign up on an excel sheet for one of three dates – 1, 8, 15 July 2021 – dependent on their availability, with a maximum of six slots to fill on each date. Therefore, the groupings were random depending on the date chosen by the participant. A range of academic levels were represented, with PhD students, post-docs, senior lecturers, and professors taking part. Thirteen people participated in total, along with an assistant moderator, Simone Gristwood. The student was the moderator, asking questions, however, Krueger (2014) suggests it is useful to have an assistant moderator to help with logistics and taking any notes during the sessions. Simone was responsible for recording, occasionally clarifying responses and providing advice to the author as she had prior experience of conducting focus groups. In hindsight, although useful, an assistant moderator was not essential.

The groups were held online, so the number of participants was limited to six to ensure that everyone would be able to participate. All groups were conducted using Microsoft Teams and the sessions were recorded using the inbuilt software. Each group lasted about one hour. The results and analysis are presented in chapter 6. The participant labelling used in the chapter is shown in Table 7.

Table 7. Focus Group Participants – DSNE

Focus Group	Date	Participant	Academic Level	Participant label
Focus Group 1	1 July 2021	1	Postdoc	FG1-P1
	1 July 2021	2	PhD student	FG1-P2
	1 July 2021	3	PhD student	FG1-P3
	1 July 2021	4	Professor	FG1-P4
	1 July 2021	5	Postdoc	FG1-P5
Focus Group 2	8 July 2021	1	PhD student	FG2-P1
	8 July 2021	2	Professor	FG2-P2
	8 July 2021	3	Postdoc	FG2-P3
	8 July 2021	4	Senior Lecturer	FG2-P4
Focus Group 3	15 July 2021	1	PhD student	FG3-P1
	15 July 2021	2	Postdoc	FG3-P2
	15 July 2021	3	Postdoc	FG3-P3
	15 July 2021	4	Senior Lecturer	FG3-P4

It should be noted here that there is likely to be a bias in the participants, with those agreeing to take part having more interest in the subject area of uncertainty. A script of questions had been prepared in case prompts were required (see 0) however, each group was different, with some needing more direction than others.

4.4.2 Transcription

All interviews and focus groups were transcribed by the author (except in the CEEDS study as already mentioned). Although this is time-consuming and can be seen as quite laborious, it was useful for initial data familiarisation. Riessman (1993) states that it provides an opportunity for early familiarisation of the data, and in this case for thematic analysis Phase 1 (see Figure 13). Bird (2005) argues that it should be 'a key phase of data analysis within interpretative qualitative methodology' (Bird, 2005; p227, cited in Braun and Clark, 2006). Additionally, as the transcription was carried out between the interviews and focus groups, it formed part of the iterative research process, allowing for additional questions to be incorporated into subsequent interviews and focus group sessions.

4.4.3 Data coding and analysis

Once transcribed the data from all the studies were 'coded', drawing out relevant, and commonly occurring, words and phrases, which could then be drawn together into themes (see Appendix I for the themes discussed in chapter 5; Appendix J for the themes discussed in chapter 6; Appendix K for the themes discussed in chapter 7). This was initially done using different colours to highlight text, but the number of codes became cumbersome, so all the transcripts were uploaded into, and coded using the software package *Atlas.ti.* This is sophisticated qualitative analysis software and was not used to its full potential in this study. However, it was very useful for managing the documents and codes. Codes were stored so that they could be easily allocated to text. This provided the ability to add multiple codes to the same piece of text, speeding up the coding process. An example of a list of codes and quotations in Atlas.ti is shown in Figure 15.

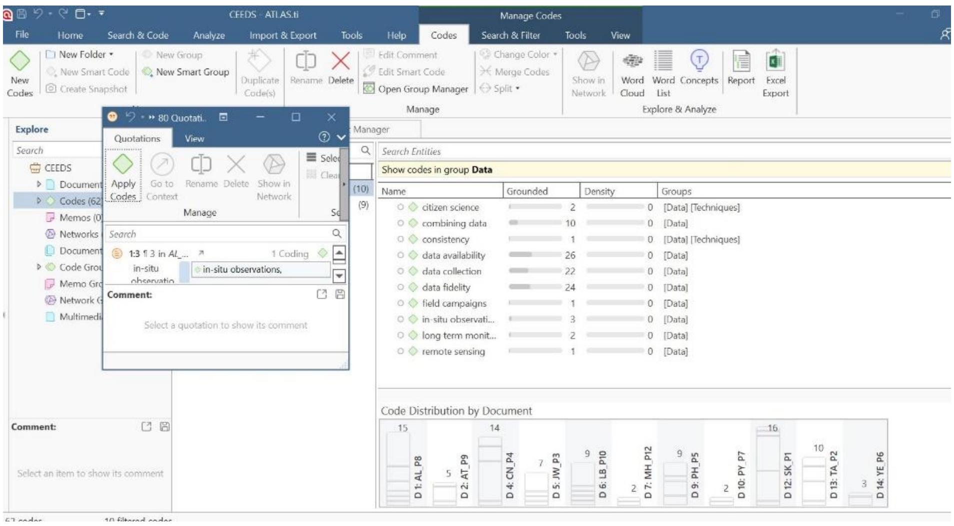

Figure 15. Example of coding using Atlas.ti

Coded data was then extracted from Atlas.ti into Excel, providing a spreadsheet of data, with each different code allocated to separate sheets which included participant information and associated text (see Figure 16). Seeing all the data in this way was invaluable. In particular, it made it possible to identify overlapping codes and was useful when looking for quotes to highlight particular themes during the writing process. Quotes were edited to remove duplicate words and irrelevant language (e.g. 'you know').

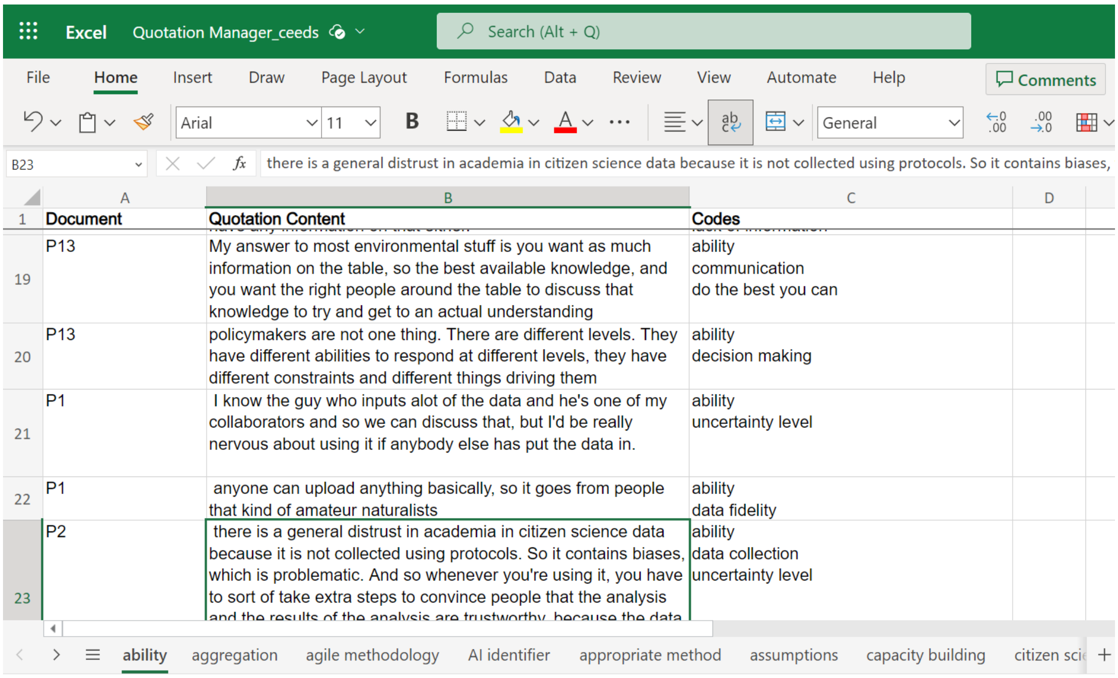

Figure 16. Example of extracted quotes and codes in Excel

Although Figure 13 shows the thematic analysis, reflection and thesis writing as separate phases, in practice these are intertwined. This is a recognised development of the analysis (Braun and Clarke, 2013). Much of the initial writing used the data to provide a descriptive analysis, however, re-reading and reviewing this produced the realisation that other meanings could also be attributed to what the participants were saying, enabling a richer analysis to develop through the writing process. Parallel to this was the literature review, which also helped to develop themes and situate some of the discussions within a wider context. The outcomes from the three research studies are presented in chapters 5, 6 and 7.

For the original collaborative CEEDS study with Lauren Thornton, all the quotes were added to Lucidchart© after individual data-driven coding. This online platform enables collaboration by sharing notes, charts, and diagrams. The codes were collated, refined, and condensed into themes. This collaboration and amalgamated data have not yet produced any outputs. The individually coded data from the interviews have provided data for the individual theses.

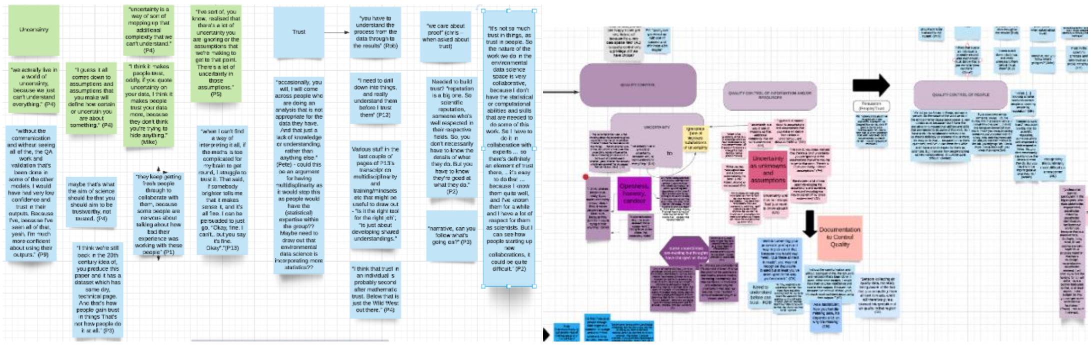

Figure 17. Example of developing themes using Lucidchart©

4.4.4 Limitations of the study

During reflection about the data collection several limitations were considered. These are:

- As noted earlier the pool of environmental data scientists is relatively small. The majority of the participants approached were employed by universities and an independent research institute in the UK, so they were from a similar research background and culture. However, the participants provided expertise from different aspects of environmental data science research (as shown on Figure 14) over a range of academic levels. Interviewees discussed their experience of the uncertainties in their research and similar details emerged indicating that saturation of data was achieved.
- One potential limitation for the focus groups was the potential power dynamic with having a mix of academic levels. This could have led to some early career researchers being more conscious of expressing their views with more senior staff listening. Alternatively, having staff that were more senior aiding the

conversation may have led to more rich and interesting discussions. Ultimately, it is difficult to say if either of these scenarios affected the data.

- By providing anonymity to interviewees, it is difficult for the reader to judge the expertise of the CEEDS interview and DSNE focus group participants. However, without providing this option some interviewees would have been reluctant to take part.

4.5 Conclusion

This chapter has introduced different philosophical values that affect academic research. These are dependent upon a researcher's disciplinary background and provide a reason for why these different understandings can create a source of tension in cross-disciplinary groups.

Building on the multi-disciplinary literature review, semi-structured interviews and focus groups were conducted to understand how uncertainty is navigated by experts involved with environmental science and environmental data science research. An inductive, thematic approach has been used to analyse the interview and focus group data to investigate the research questions set out in the thesis introduction. The experts who took part in the studies provided a wide range of lived experiences providing rich information for the different points along the data-to-decision pathway:

- Data – data collection by environmental scientists, and data managers
- Analysis – statisticians, environmental modellers, computer scientists
- Narrative and Messaging – all participants
- Interpretation – all participants
- Decision – extrapolated from involvement of some interviewees with policy and/or decision-making.

Analysis of the data and the subsequent themes are discussed in the following chapters — starting with the historical case study of ozone depletion study in chapter 5, followed by studies into contemporary environmental data science with DSNE focus groups in chapter 6 and CEEDS interviews in chapter 7. These three studies provide a complementary picture of the different aspects of uncertainty in environmental scientific research. The ozone study looks at uncertainty and decision making, the DSNE study considers uncertainty, and the challenges presented by different understandings of what it means, and the CEEDS study builds on this to consider how these challenges can be overcome to enable environmental data science to move forward. The different aspects of uncertainty from each of these chapters (summarised in each chapter conclusion) are then amalgamated to develop the typology of uncertainties relevant for environmental data science in chapter 8, which was introduced in chapter 3.

5 The ozone depletion story: A tale of data, uncertainty and risk

5.1 Introduction

This case study looks at stratospheric ozone depletion, a specific environmental challenge that required urgent global policy action in the 1980s. It provides a retrospective study of a historical scientific problem, which started with uncertain scientific hypotheses and a limited body of evidence, eventually feeding into an urgent decision-making process. Scientists had to move from the normal science of hypotheses and associated data collection, out of their disciplinary silos, to working with other scientific disciplines to provide evidence for why the ozone layer was disappearing. Alongside this, some scientists were thrust into the world of scientific assessments, policy, legislation and uncertainty. Consideration of how this problem was handled provides insights into how scientists respond to the demands of this type of complex (global) environmental problem, which could be applied to contemporary challenges.

The destruction of the Earth's protective ozone layer by man-made chemicals has been an important global environmental challenge for the past 50 years. This challenge is a relatively stand-alone problem and provides a longitudinal study that has experienced many different scientific uncertainties, alongside differing opinions and narratives about the sources of the ozone destruction. Despite these uncertainties, global policies for action were agreed and continue to be updated, with recent studies showing that the ozone layer is beginning to recover (Pyle *et al.*, 2022).

Based on a literature review and interviews with atmospheric scientists and those involved in the decision process at the time, the study looks at how the uncertainty was navigated, the production of scientific consensus, and considers if there are any lessons to learn from this story that are relevant for contemporary scientific research.

5.2 Summary of method

This case study consists of a literature review combined with six semi-structured interviews. Ethics approval for the study was obtained and can be viewed in Appendix A. The interview participants were purposively selected providing expertise on the subject area gained over a long period of time. There was also an element of convenience as some were known to the author through previous employment (as described in chapter 4) and others are/were academics at Lancaster University. These six interviewees provided a rich source of data for this study, many have been involved at a high level with translating science for policy to enable decision-making, and several have been involved in this research area for over 50 years. Their experiences particularly contribute to the decision aspects of the data-to-decision pathway. A summary of the interviewees and their specialist areas is provided in Table 8, and further details about their expertise follow this. Participants signed a consent form agreeing to take part in this study and they were given the option to be named or remain anonymous. The ability to name interviewees provides additional credibility to the study as it enables a description of their expertise to be included.

Discussions initiated by the interview questions (see Appendix E) included looking back to the science and decision-making during the 1980/90s, general thoughts on uncertainty, and uncertainties the interviewees have experienced. All interviews were recorded, transcribed, and thematically analysed by the author. Themes drawn out from these discussions consider the impacts on the scientists of working on a high-profile environmental problem and at the boundary between science and policy and are included in Appendix I.

The chapter is a mixture of literature review and interview data. To clarify, section 5.3 provides background details from literature; 5.4 on the sources of uncertainty, mainly based on literature but supplemented with quotes from the interviews; 5.5 on the transition from science to policy, again based mainly on literature with a few interview quotes; 5.6 on providing scientific advice, based mainly on the interviews; 5.7 is based on the interviews.

Table 8. Summary of interview participants and their specialist area

Interviewee	Date of interview	Specialism
John Pyle	12.12.19	Atmospheric chemist and modeller
Oliver Wild	17.03.20	Atmospheric process modeller
Paul Young	06.04.20	Atmospheric scientist
Neil Harris	22.04.20	Atmospheric chemist and policy advisor
David Warrilow	02.10.20	Senior government science advisor and international negotiator on climate change (retired)
Anon	17.03.21	Atmospheric chemist

Interview participants

Professor John Pyle CBE FRS – Director of the Centre for Atmospheric Science, Cambridge University (when interviewed). As one of the world's leading atmospheric chemists, his research has played a key role in providing scientific advice to the UK government and international bodies around policies related to atmospheric pollution and climate change. As a pioneer of atmospheric chemical modelling, he contributed to understanding ozone depletion as the problem emerged. He is a Co-Chair of the Scientific Assessment Panel of the Montreal Protocol.

Professor Oliver Wild FRMetS – Lancaster Environment Centre. Oliver's interests are in atmospheric composition, chemistry, and transport, and in understanding how natural and anthropogenic emissions of trace gases affect regional air quality and global climate. He has spent more than 25 years developing and applying numerical models of atmospheric processes over a range of scales from urban to global.

Dr Paul Young – Lancaster Environment Centre (when interviewed). Paul is a climate scientist, using computer models and observations to understand the composition and climate of the atmosphere. He is interested in how the climate, greenhouse gases, air quality and the ozone layer can be studied using data science techniques, as well as how these problems intersect with society. He is a member of the Scientific Steering

Committee for the IGAC/SPARC (Stratosphere-troposphere Processes and their Role in Climate of the World Climate Research Programme) Chemistry-Climate Model Initiative. He is an author on the 2018 and 2022 WMO Scientific Assessment of Ozone Depletion reports.

Professor Neil Harris – Cranfield University. Neil is experienced in the international coordination of atmospheric research and in ensuring that the understanding gained is transferred to the policy and public fields. He is co-chair of SPARC and has been involved for many years with international assessments of ozone depletion and climate change. As an expert on issues related to stratospheric ozone depletion, climate change and air quality, Neil provides expert advice to policymakers around the world.

David Warrilow OBE FRMetS – President of the Royal Meteorological Society 2019/2020. Now retired, David was formerly a senior government science advisor and international negotiator on climate change and environmental issues, such as ozone depletion and air pollution. He managed a significant research programme at the Department of Energy and Climate Change providing underpinning scientific evidence and analysis of climate change, energy and ozone depletion in support of the UK's domestic and international policies.

In addition to the five people listed above, a further interview was held with a scientist who wished to remain anonymous. They were an early career researcher working in ozone chemistry at the time of the ozone hole discovery.

5.3 The ozone story

5.3.1 Background

Ozone forms a protective layer approximately 15-35 kms above the Earth in the stratosphere. Its presence was discovered in 1912 by French physicists, Fabry and Buisson. Ozone occurs naturally in the stratosphere and is highly reactive, it is constantly being destroyed and created by chemical reactions due to ultraviolet radiation (UV) from the sun, so the thickness of the 'layer' naturally varies seasonally and geographically. The ozone layer protects organisms on Earth from the harmful effects of

UV radiation, so any prolonged decrease in ozone would affect human health, for example, leading to increased rates of skin cancer and cataracts in humans (c.f. Harm, 1980).

In the 1960s, it was suggested that the ozone layer could be damaged by water vapour and nitrogen oxides from supersonic aircraft (which fly at a higher altitude than other aircraft) (Oppenheimer *et al.*, 2019). Although it was decided that this was unlikely to happen it started to raise awareness of other potential routes of damage. For example, a study by Stolarski and Cicerone (1974) suggested that chlorine monoxide from volcanoes or solid fuel rockets could destroy ozone if significant quantities reached the stratosphere.

Atmospheric concentrations of man-made compounds, chlorofluorocarbons[17] (CFCs), were measured by Lovelock, Maggs and Wade (1973) during a voyage from the UK to Antarctica. This research raised the curiosity of Sherry Rowland as to where these may be ending up (Harris, 2020), leading to Molina and Rowland (1974) calculating that the breakdown of halogenated hydrocarbons (including CFCs) could create the source of chlorine in the stratosphere that Stolarski and Cicerone had been seeking. Process models were then developed to estimate the effect of these hypotheses (Cadle, Crutzen and Ehhalt, 1975). The importance of this research was recognised in 1995 when the Nobel Prize in Chemistry was awarded to Paul J. Crutzen, Mario J. Molina and F. Sherwood Rowland "for their work in atmospheric chemistry, particularly concerning

[17] Halogenated hydrocarbons (chlorofluorocarbons [CFCs] and bromofluorocarbons or halons) are gases developed by Thomas Midgley for refrigeration in the 1920s. Prior to their development, refrigerant gases were toxic and flammable, whereas these new CFCs (initially manufactured by DuPont in the USA who called them Freon) were harmless to people and inert at ground level. Their use increased to include air conditioning and as a propellant in aerosol sprays. This latter use grew in the 1960s and 1970s and became the largest use of these chemicals. The gases are released immediately from aerosols, however, when used as refrigerants or in air conditioning they are not released until the item is no longer in use. It takes 3-5 years for the gases to reach the stratosphere and become broken down by solar radiation (c.f. Roan, 1989; Andersen and Sarma, 2002).

the formation and decomposition of ozone" ('The Nobel Prize in Chemistry 1995', Royal Swedish Academy of Sciences, 1995).

In 1985, British Antarctic Survey scientists, Joe Farman, Brian Gardiner and Jonathan Shanklin, published a paper describing large decreases in stratospheric ozone levels over Antarctica from a ground-based instrument (Farman, Gardiner and Shanklin, 1985). This was a big surprise to scientists working in the field, as models hadn't predicted such large decreases, nor this location for ozone loss to occur (Oppenheimer *et al.*, 2019). This finally provided proof that the ozone layer was being destroyed and provided evidence to support the legislative process.

Currently it is predicted that the ozone layer should fully return to pre-1980 levels by 2066 (WMO, 2022). This date is for Antarctica which is predicted to be the last area to recover, with the Antarctic 'ozone hole' still occurring each year at some point between September and December (the Austral spring). The size of the 'hole' varies due to the stratospheric temperature, which affects the creation of small ice particles, known as polar stratospheric clouds, on which the chemical reactions occur. This variability has been highlighted in recent years with 2019 seeing the smallest ozone reduction since 2002, whereas 2020 and 2021 have seen large and long-lasting 'holes' (WMO, 2022). Additionally, observations in Spring 2020 saw a 'hole' appear for the first time over the Arctic due to cooler than usual temperatures during the Arctic spring (Witze, 2020). Ozone levels are also affected by natural climate cycles, such as solar cycles, the quasi-biennial oscillation (changes in direction of winds in the stratosphere above the equator), the El Nino southern oscillation and even rainfall patterns. As well as climate variabilities, unpredictable natural events can also affect the stratosphere, such as a large volcanic eruption, powerful enough to send ash up into the stratosphere, e.g., Mount Pinatubo in 1991 (Brasseur and Granier, 1992). Another example is the extensive forest fires which occurred in Australia in 2020, these were particularly intense with smoke causing increased aerosols in the stratosphere (c.f. Hirsch and Koren, 2021). These latter unpredictable natural events show some of the unknown uncertainties that can affect the stratosphere, creating a source of ignorance for researchers, which in turn makes modelling ozone recovery more challenging.

5.3.2 The road to legislation

Although there were many uncertainties about the mechanisms of ozone destruction and the extent of any damage, concern about the issue was taken seriously and the first international committee on ozone depletion was formed by the United Nations Environment Programme (UNEP) in 1977. Public awareness of environmental problems was increasing at this time, particularly following the publication of Rachel Carson's book 'Silent Spring' in 1962 (Andersen and Sarma, 2002).

The first draft of an international agreement occurred in 1982, becoming the United Nations Vienna Convention for the Protection of the Ozone Layer which was signed in March 1985. This Convention called for more ozone research but there were no requirements for reduction in the manufacture of CFCs at this time. In 1987, the Montreal Protocol on 'Substances that Deplete the Ozone Layer' was signed by 30 countries agreeing to restrict production of CFCs. By the time this was ratified the legislation came into force on 1 January 1989. In order to account for uncertainties and the continuation of research, it was agreed that the Montreal Protocol would be reassessed every four years, based on international scientific assessments. There have been several amendments to the Protocol, the most recent in 2016 was the Kigali Amendment, which set schedules for phasing out global production and consumption of certain hydrofluorocarbons (HFCs), originally developed as CFC replacements, and came into force in 2019. The Montreal Protocol is often praised as an example of a successful science-based policy (Oppenheimer *et al.*, 2019) and "the most successful environmental treaty in history" (D.Fahey, reported in Milman, The Guardian, 2023).

In her book 'Ozone Crisis', Sharon Roan (1989) describes the reaction of US states to the 1974 Rowland/Molina theory, with Oregon being the first US state to ban CFCs in 1975. The USA introduced legislation to stop the manufacture of non-essential CFCs by 15 October 1978, although non-aerosol CFCs didn't get regulated and were used continuously into the 1980s. However, European countries were much slower to react (Farman, 2002). In the UK it has been suggested that due to her chemistry background Margaret Thatcher understood the significance of the problem and endorsed the legislation ('Saving Planet Earth: Fixing a Hole', 2018). Despite the many scientific unknowns and uncertainties, global legislation was agreed – described as an example of the precautionary principle by Richard Benedick, the US chief negotiator for the Montreal Protocol (Farman, 2002).

Two weeks after the Montreal Protocol was signed, the scientific data from the Airborne Antarctic Ozone Experiment (AAOE) was released, showing that when quantities of ozone were low, quantities of chlorine were high, confirming the hypothesis that CFCs were causing the ozone destruction (Solomon, 2019).

Throughout this period, data collection and its analysis, along with the application of models, played a major role in understanding and predicting the outcomes of this challenge but although these were beset with uncertainties, decisions were made. The following section continues to draw on examples from literature, alongside examples provided by the interviewees in response to the interview questions.

5.4 Sources of uncertainty

5.4.1 Data collection

A simple instrument to measure stratospheric ozone from the ground was developed by the Oxford University physicist, GMB Dobson, in the 1920s, following a suggestion by Fabry and Buisson that it would be interesting to measure daily ozone levels (Dobson, 1968). The Dobson spectrophotometer, known as the 'Dobsonmeter', measures the amount of ozone in an upwards column, called the Dobson unit. A worldwide network of these ozone spectrophotometers was established as part of 1957-58 International Geophysical Year, with responsibility for data collection passing to the World Meteorological Organisation (WMO) in 1957. It was one of these instruments, installed at Halley Bay on Antarctica, which provided the data for the Farman *et al.* (1985) 'ozone hole' paper. A network of ground-based instruments to measure ozone, including about fifty Dobsonmeters, continue to record data to the present day (WMO, 2022). This early research into the ozone layer remained within the remit of physics and meteorology.

From 1978, the Total Ozone Mapping Spectrometer (TOMS) instrument, on board the US National Aeronautics and Space Administration (NASA)'s Nimbus 7 satellite, also collected ozone data. This instrument enabled the creation of global maps of ozone distribution. However, the low levels of stratospheric ozone seen over Antarctica had not been picked up from the satellite-based data collected. Following publication of the Farman *et al.* (1985) paper, Stolarski reassessed the satellite data finding that the computer code was programmed to reject very low readings as errors, so scientists had ignored the data assuming the instrument was faulty (Oreskes and Conway, 2010). Attributing unexpected results to faulty instrumentation is a recurring theme in this story. The Farman *et al.* (1985) paper could potentially have been published sooner, but as low ozone levels over Antarctica hadn't been predicted their initial reaction was that the Dobsonmeter was defective (Andersen and Sarma, 2002). Both the satellite and ground-based instruments collect a large volume of data. Christie (2001) suggests that as these data collections were seen as routine, and as no large ozone losses had been predicted, it was not seen as urgent to process the data creating a backlog and a delay in finding the evidence for ozone destruction.

Following publication of the Farman *et al.* (1985) paper, there was a large increase in funding in order to investigate the mechanisms causing the ozone depletion, with NASA and National Oceanic and Atmospheric Administration (NOAA) organising field investigations in Antarctica, August to September 1986 – National Ozone Experiment (NOZE); August to September 1987 – NOZE II and Airbourne Antarctic Ozone Experiment (AAOE). The latter involved two aircraft fitted with several different scientific sensors providing data that hundreds of scientists looked at in real time (Roan, 1989). These field experiments led to the rapid development of new instruments and a need for scientists from different disciplines to work together, adding chemists to the meteorologists and physicists already studying the problem.

Attention also turned to the possible occurrence of ozone loss over the more populated Arctic regions. The European Commission, National Governments and Institutions around Europe funded research to understand what was happening to ozone in this region. The European Arctic Stratospheric Ozone Experiment (EASOE) took place over the winter of 1991/92 (c.f. Pyle *et al.*, 1994), followed by the Second European Stratospheric Arctic and Mid-latitude Experiment (SESAME) during 1994 and 1995 (c.f.

Amanatidis and Ott, 1995; Europäische Kommission, 1997). Meanwhile US scientists continued to look at processes in the southern hemisphere.

Stratospheric ozone research is ongoing, with monitoring data collected from satellites, ground-based instruments, and instruments on aircraft. Although ozone depleting substances (ODS) are controlled by the Montreal Protocol, monitoring of ozone levels continue to make sure that the Montreal Protocol is being adhered to and is leading to a recovery of the ozone layer. This continued monitoring captured an incidence of illegal manufacture of CFC-11, with measurements showing CFC-11 concentrations had stopped reducing from 2012. Further research suggested that production of new chemicals was taking place in China (Montzka *et al.*, 2018). This highlights the necessity of continued measurements to monitor compliance with the legislation, as it is not guaranteed that all people/businesses will adhere to the regulations.

In spite of this, consideration of data uncertainties have not been a priority until relatively recently. Several reviews of ozone recovery have been published for the 30th Anniversary of the Montreal Protocol in 2017. One by Chipperfield *et al.* (2017) agrees that the Protocol has led to a decrease in ODS, however, due to links with greenhouse gases there is still some uncertainty as to when levels of ozone in the stratosphere will return to pre-1980 levels. This paper also reviews the sources of uncertainties that need consideration when looking at observations of ozone levels:

- The measurement technique
- Data sampling
- Uncertainties introduced by the regression (the statistical relationship of ozone recovery to other variables, potentially necessitating assumptions to be made in order to carry out an analysis)
- Uncertainties from data preparation
- Differences between trends from different observation systems.

The authors state that the first two are 'relatively well understood' but concede that the other three have only recently started to be considered (Chipperfield *et al.*, 2017; p213). The latter uncertainty is exemplified by a trend analysis paper, with 41 authors, which describes the problems of combining datasets (Harris *et al.*, 2015). During the interview for this thesis on 22 April 2020, Neil Harris, the lead author, described the difficulty in getting co-authors to agree on how they should present uncertainty:

> *"what we mean by uncertainty and how well scientists really understand true uncertainty in a complicated system - and I think they generally underestimate the uncertainty in it - as it was quite a hard argument to get all the co-authors to agree that [how to quantify the uncertainty and provide a value] in that paper, and they were much more able mathematically than I am, it is just that I had thought about the assumptions and they hadn't, where as they think about the maths"* (Harris, 22.04.20).

The quote shows how the different uncertainties and understanding of uncertainties require compromises, between authors from different disciplines, to get the work published. Both examples reveal that consideration of data uncertainties are becoming increasingly important in this scientific field.

In 2016, the WCRP/SPARC created the Long-term Ozone Trends and Uncertainties in the Stratosphere (LOTUS) group with various objectives, including the need to improve understanding of sources of uncertainties in ozone trends and to investigate how uncertainties interact and propagate through the different stages of the analysis chain (SPARC/IO3C/GAW, 2019). Some of the sources of uncertainties the report highlights are:

- Aging instrumentation
- Changes to instruments and/or calibration procedures
- Changes associated with the satellites, such as drift or movement due to aging
- Merging data due to a lack of continuous global datasets, for example, since 1984, ozone concentrations have been collected from nine different instruments on seven satellites.

These uncertainties highlight the problems of data consistency and comparability caused by changing instrumentation, particularly when research is required to monitor the continuing effectiveness of legislation, like the Montreal Protocol.

Alongside data collection, prediction of future trends has led to the development and use of atmospheric models. Three of the interviewees are atmospheric modellers, so the next section incorporates the uncertainties they have experienced alongside details from the literature.

5.4.2 Atmospheric models

In the early 1980s, the atmospheric chemistry and transport models used to make predictions were relatively simple due to limited computing power. As computing power has increased these models have become much more complex, with 2-D and 3-D models developed to account for the effects of circulation (Edwards, 2010). Different types of atmospheric models have been developed, such as chemical-transport models and chemistry–climate models and are used to predict when the ozone layer will 'recover' or return to the level recorded in 1980 (Chipperfield *et al.*, 2017). These computer models provide a powerful tool to understand the atmospheric processes, or to provide scenario analyses for future changes, however as stated by Pyle (12.12.19): "you've always got to come back to the fact that this is a model, so I think you've always got to be asking yourself questions about how faithfully the model can reproduce all the processes that are going on". This quote acknowledges that some modellers are aware that the results from using these models contain a certain level of uncertainty.

Although models have improved, they are only as good the inputs. Computing resources were cited as a source of uncertainty by interviewees. Young (06.04.20) stating: "you have to make lots of approximations, depending upon what kind of computing resources you've got available to you" and Wild (17.03.20) "it's a compromise between what you'd like to have in there, the kind of accuracy side of it, and what's computationally feasible and what is worth the effort". Pyle (12.12.19) concludes that "most modellers that I know would recognize that their models have got limitations, but whether they always convey that every time they message to do with their model, that's a different matter".

This point about communication of model limitations is interesting as it could lead to an assumption of certainty, or reduced uncertainty, of the research user. This returns to Mackenzie's certainty trough (Mackenzie, 1990) discussed in chapter 3 (section 3.2.3). The quotes above can be mapped onto the levels of uncertainty reported by Mackenzie, with the research producer knowing the limitations and therefore having some uncertainty about the results they are producing. However, if they don't acknowledge or communicate the limitations then, as mentioned, the research user will be unaware of these uncertainties and have more confidence about the results. This agrees with the findings of Shackley and Wynne (1996), who also refer to Mackenzie's certainty trough in a study of climate modellers who use general circulation models. Modellers are credited with recognising their models' uncertainties but suggest that awareness of these limitations and uncertainties is reduced in those using the outputs (Shackley and Wynne, 1996).

A further potential source of communication error, again reducing the level of uncertainty of the research user, is the conception that different models are independent. This supports the common assumption that similar results produced by different models provide an indication of consensus of predictions. However, although different institutions have developed their own versions of these models, these are not necessarily independent. One interviewee mentioned that due to the movement of researchers between different institutions, knowledge would be taken from one modelling group to another, and input into different models around the world (Young, 06.04.20). This interdependence of models is also noted by Knutti *et al.* (2013) who discuss the genealogy of climate models and argues that when multi-model ensembles are interpreted the overlaps between models are rarely acknowledged.

Many of the scientific uncertainties discussed in this section are relevant to contemporary scientific research and the provision of evidence from data to back up legislative action. However, in the early days of this story precautionary decisions were based on scientific theories and the agreement of the global political community that due to the potential risks to life, and particularly human health, urgent action was required (Benedick, 1991). Over time more research provided data to enable more informed decision-making. This created a new role for many scientists and as discussed in chapter 3, the boundary between science and policy became blurred for some scientists.

5.5 From science to policy

A major feature of global environmental challenges is the use of scientific research to make policy decisions. This section explores the impact of the decision-making process on different groups of stakeholders by combining literature with the experience of some of the interviewees. The production of scientific assessments based on the consensus of the academic community emerged from the literature review as a major decision-making tool, but the reality of constructing these documents became apparent from the interviews. The decision process in this ozone story was also influenced by industry, and the impact of those that tried to sow doubt in the science.

5.5.1 Academic stakeholders

- **Scientific Assessments**

As mentioned in section 5.3.2, the Montreal Protocol is reviewed at a meeting of Governmental representatives every four years, based upon the WMO organised scientific assessment of the most recent research. The first report was completed in 1981 and the most recent in 2022 (WMO, 2022). Reassessment of the scientific evidence every four years was incorporated into the Montreal Protocol in recognition of uncertainties: “to cope with the complex changing state of scientific knowledge” (Oppenheimer *et al.*, 2019; p119). Lambright (1995 cited by Oppenheimer *et al.*, 2019) described allowing for future revisions based on updated research as an example of an adaptive management framework. These WMO assessments are carried out by a group of invited international scientists overseen by a scientific steering committee, which provides the scientific consensus important for policy legitimacy (Van der Sluijs *et al.*, 2008). An Executive Summary, written for policymakers, highlighting the most important scientific agreements and providing “a single voice”, accompanies the reports (Oppenheimer *et al.*, 2019; p117).

Regular scientific assessments are an important communication tool to provide a scientific consensus for decision-making. However, getting to an agreement is not necessarily an easy path. The composition of the groups can be difficult, particularly with “individuals who want to push their thing because everybody would like their work highlighted in the assessment” (Pyle, 12.12.19). Harris (22.04.20) described his experience of working on assessments with “clashing of egos” and “personal rivalries” making consensus difficult, concluding “some people will just want to understand the truth, others will want to be right”. Pyle (12.12.19) concludes that these issues are overcome by “first of all [having] a group of people, but then secondly, [with] the kind of steering group above that is that you hope that you're going to kind of filter that out”. Even so, Harris (22.04.20) states: “the whole point of an assessment is to get different viewpoints confronting each other and coming to a logical and preferably agreed conclusion...people trying to agree on how much you can say with confidence”, highlighting that the discussions from differing viewpoints aid agreement. Although Pyle (12.12.19) does concede that “the problem with an expert view, of course, is that they may have it wrong, just because the majority think one thing doesn't necessarily mean it's right, and there are biases, conscious or unconscious. I think both of those things are potentially an issue. I think by and large we handle them quite well, but you've got to recognize that that's a possibility”. It is clear that although consensus of experts is a way to control uncertainties, as discussed in chapter 2, getting to this consensus needs managing and remaining aware that not all uncertainties will be resolved. Oppenheimer *et al.* (2019) report that in more recent assessments the lead authors are chosen because they are recognised experts in their chapters’ field, as well as strong communicators and team-builders.

One issue with the scientific assessment process not generally discussed is the pressure to get research published as the next assessment round approaches, so that the research can be considered for inclusion. One interviewee mentioned how he felt rushed to get a paper submitted in time and that he thought the analysis could have been improved (Young, 6.4.20), providing evidence of another place where uncertainty could arise, if an analysis is not as rigorous as possible. This highlights the prestige of having research included in the reports but provides an example of a clash between normal science and research for policy-relevant science. Therefore, if peer-review is necessary to provide confidence in research for decision-making then the peer-review process needs to become faster under post-normal science.

- **Funding**

Prior to the discovery of the 'ozone hole' atmospheric research was carried out by a relatively small group of scientists, so the pool of people involved with the early reports was small. However, Solomon (2019; p1) notes that the Farman *et al.* (1985) 'ozone hole' paper changed the direction of research and the "careers of hundreds of scientists". It led to increased amounts of funding available from some national governments and international organisations.

The direction of research is also influenced by the academics themselves. In Europe, the European Commission established a stratospheric ozone research programme in 1989, which consisted of an Advisory Science Panel, part funding of the European Ozone Research Coordinating Unit (based at Cambridge University) and funds for research. Research funds were targeted at establishing increased collaboration, communication and coordination across Europe, as well as for setting up monitoring networks and large field campaigns. There are areas of bias within this system, with members of the Science Panel benefitting from pushing forward their areas of research and being included on funding proposals.

5.5.2 Industry stakeholders

The major manufacturers of the chlorofluorocarbons, DuPont in the USA and ICI in the UK, played a major role in this story. As well as the WMO assessments, other reporting groups were established in the mid-1980s and included industrial peers. The International Ozone Trends Panel was formed in 1986 to analyse global ozone levels from the ground based and satellite data and among the members of this panel was Mack McFarland, a scientist employed by DuPont in the USA (Oppenheimer *et al.* 2019). In the UK the Stratospheric Ozone Review Group (SORG), established by the Department of the Environment in 1985, wrote seven reports up to 1999. Alongside around 12-14 UK researchers, the group also included Archie McCulloch from ICI as an observer. Initially the CFC manufacturers pushed back against the theories, but with the inclusion of industrial scientists on these panels these companies were aware of the research being carried out. Alongside this, they were developing alternatives for CFCs — hydrochlorofluorocarbons (HCFCs). The following quote from interviewee David Warrilow (02.10.20), a scientific advisor at the UK Department of the Environment (as it was at that time) summarizes their mindset: “industry is always doing these things [lobbying], trying to buy time because they know the game is up, but they want to put it off as long as possible till they’ve got another something else in place and basically they got to the view that they could make money out of HCFCS so it didn't matter as long as they kept business running”. This confirms the argument of Gareau (2010) that the chemical industry accepted the Montreal Protocol once they had developed replacements for CFCs. On 18 March 1988 Du Pont agreed to stop the manufacture of CFCs within ten years, followed by ICI later that year.

5.5.3 Doubters

The science of ozone depletion was not without its critics. In their book, *Merchants of Doubt*, Oreskes and Conway (2010) discuss the negative impact of some scientists who were sceptical about research outside their domain and presented alternative theories. For the ozone issue, the main proponent of this was Fred Singer, an atmospheric physicist and serial denier, who started with acid rain, moving on to ozone depletion and passive smoking. He wrote many articles for the US mainstream press and so had a wide readership for his argument that the ozone hole wasn’t caused by CFCs. He did not present any quantitative evidence for his claims, purely aiming to undermine the scientific research to sow doubt and solicit an emotive response from the readership (Oreskes and Conway, 2010). In his opinion, uncertainties in the science such as problems with instrumentation provided a reason for inaction, and he suggested that the scientific community were corrupt. Additionally, Singer suggested that replacing CFCs would be difficult, dangerous, and expensive, potentially reflecting the suggestion that he received funding from industry, although this remained undisclosed (Oreskes and Conway, 2010). Oreskes and Conway (2010) describe how Singer and other scientists’ twisted information to produce ‘credible’ explanations for what was happening, and this misinformation gained some momentum in the early 1990s. Joe Farman spent a lot of time explaining to the media why the claims of Fred Singer were incorrect, providing evidence for the scientific research and discussing the research evidence with Singer himself. Despite being retired by this time, Joe came into the office nearly every day and had time to counter these alternative viewpoints. In the end, as the CFC manufacturers did come up with alternatives and agreed to stop CFC production, it left little for the doubters to pursue, so they moved on to climate change (some of whom were responsible for Climategate discussed in chapter 2).

5.6 Providing scientific advice – a risky business?

It became clear when reflecting on the interviews for this case study that these complex environmental challenges, which require policy action, rely heavily on the input and compliance from scientists and can change their relationship to the research.

The role of scientists in policy decision-making has been an area of debate in Science and Technology Studies (STS) for many years (c.f. Jasanoff, 1994; Gieryn, 1995). Grundmann (2006) notes that scientific research aids policy decisions by a linear "information transfer" from science to policy, allowing policymakers to emphasise the role of scientists and place responsibility for action onto the scientists (as seen by the 'follow the science' rhetoric of the UK Government during the Covid pandemic – c.f. Colman *et al.*, 2021). As Litfin (1994; p1) notes they become a "political actor in their own right". Introduced in chapter 2, this 'blurring of boundaries' can create problems, or opportunities, for scientists, depending on their preference. This section discusses the experiences, perceptions and responses of the interviewees to their involvement with an environmental problem that required/s policy intervention. The significant themes that became apparent from the interviews were impartiality, vulnerability, and credibility.

5.6.1 Impartiality

Scientific research which propels scientists to the boundary of science and policy affects their actions. The interviewees appear conscious of this boundary, with some relying on the scientific evidence to provide the message so the researcher themselves remains impartial to the decisions to be made. For example, both Pyle and Wild referred to the use of the science to 'inform' policy: "the parties to the Montreal Protocol...it's up to the parties to decide whether they want to add yet further gases to the mix, and I'm sure that the science will inform them about that" (Pyle, 12.12.19) and "models used for informing policy rather than actual policy itself…but that was again purely physical science bashing into policy" (Wild, 17.03.20). The desire to cross the boundary between presenting the research and making their views on the issue known depends on the individual. For some, there is a reluctance to cross, as noted by Harris (22.04.20) referring to a colleague: "[they] tend to be the 'No we'll report it and we'll take it as far as we can to the interface' without making [their] views public" and encapsulated by a quote from one interviewee who described being "dragged into the policy side of things" (Wild, 17.03.20). However, Young (06.04.20) is prepared to be more open: "you're not really in the political process, so I think being conscious of not being a self-advocate, but at the same time, perhaps being open about that you would prefer a solution which is socially and environmentally just". This latter comment was made because the interviewee mentioned Pielke (2007) who accuses scientists of 'stealth issue advocacy', suggesting that although scientists are focused on science they are presenting it in a way that gains a particular political response. In his quote, Young (06.04.20) is suggesting that a researcher should be transparent about their viewpoint, which would then enable a decision-maker to understand if there are any biases appearing in the message being put across. However, as discussed earlier, not all researchers share this opinion, with many scientists wishing to retain the privacy of their viewpoints and relying on the 'objectivity' of science for impartiality.

Open advocacy arises in the ozone story. Following publication of the Molina and Rowland (1974) paper in Nature, Sherry Rowland did not hide from the theoretical predictions they made and was an advocate for action, being involved with an environmental movement to stop production of CFCs (Prather and Blake, 2012). However, the paper and his advocacy produced a negative response from the chemical industry. For several years Rowland experienced personal threats (Prather and Blake,

2012) and chemistry departments in the USA didn't invite Rowland to speak for the following 10 years (Harris, 2020).

Experiences such as those described above and those of the scientists caught up by Climategate (described in chapter 2), alongside an awareness of accusations of stealth advocacy, will understandably make many scientists wary of becoming embroiled in a political/politicized debate and conscious of a need to remain impartial. However, people have different attitudes to risk (Weber and Milliman, 1997) and therefore have different attitudes to making themselves vulnerable to the resulting outcome. In this story it appears that for Rowland, the risk of not publicising the potential effect of CFCs was greater than protecting his personal reputation. So, some scientists are prepared to present their views, whereas others wish to present the research impartially.

5.6.2 Vulnerability

Remaining impartial is a means for scientists to reduce their vulnerability to personal criticism and hence to protect their reputation. However, as considered in previous chapters, one of the major challenges for scientists whose research feeds into policy decisions is what aspects of their research need to be communicated and the best way to do this so it is understood. If this is not done well it can be misinterpreted, creating confusion and criticism. Uncertainty has an impact on these communications, with Pyle (12.12.19) stating: “policymakers don't want to hear about uncertainty, they want scientists to say, ‘we're very confident…this is the way to go’”, creating a communication dilemma between remaining impartial and providing an expert opinion to inform policy. This is partly overcome by the production of scientific assessments as they provide a consensus of subject experts, which reduces the experts’ individual vulnerability.

Pyle (12.12.19) described a situation where the Co-Chairs of the WMO assessment report attended a meeting of the parties of the Montreal Protocol to explain how the importance of certain gases had been assessed "we used words like, uncertainty... and that went down incredibly badly”. Although Pyle went on to say: “what they don't want is for you to say all this is fine and then five years down the line say ‘no, it's not fine’, so they quite like the idea of being certain that if they follow a particular path that is the path to follow", however: "that's clearly an issue because you want to tell policymakers that if they do something, to gases to do with the ozone layer, or to gases to do with climate, that you want to be reasonably confident that…policy decisions that they've made are going to have some impact and they're going to have the impact that you said they're going to have" (Pyle, 12.12.19). It is under these circumstances that the scientific uncertainty and the cognitive uncertainty of the scientist converge. Several interviewees mentioned 'confidence' in results: "if we did understand it, we'd be much more confident about our answer" (Wild, 17.03.20): "people trying to agree on how much you can say with confidence" (Harris, 22.04.20): "if you get some commonality in response it gives you some more confidence" (Anon, 17.03.21): "some of that degree of confidence is based on model calculations…and some of it is based on a kind of expert view, you know, how confident do you feel?" (Pyle, 12.12.19). Therefore the uncertainties reduce their confidence in the research so scientists become cautious with their communications, e.g. "scientists…are much more cautious and are not keen on giving messages that they may need to kind of, you know, change either subtly or not so subtly in the future" (Pyle, 12.12.19): "if you are uncertain, you go more cautiously, you don't just go zooming off ahead 'cause that way you prang on a rock" (Warrilow, 02.10.20). This caution reduces their vulnerability to criticism for providing incorrect or uncertain information, however, it doesn't provide the decision-makers with any certainty about the direction they should follow. It is these circumstances that promote the adaptive style of decision-making, mentioned in chapter 2, enabling initial decisions to be made, which can then be changed as and when any uncertainties are resolved.

The scientific method of peer review helps to reduce vulnerability and provides credibility to research. However, when research has not been through this process scientists can feel vulnerable if they make statements about aspects of their research that they do not feel confident with, and that aren't backed by published research. For example, Pyle (12.12.19) confirms "no scientist wants to stand up at the meeting of the [Montreal] parties to say this is happening until they were confident that it has got through the peer review process", which provides evidence that the research has been endorsed by other scientific experts. Therefore, communication of uncertainty, as discussed above, of un-peer reviewed research, could make the scientist vulnerable to how they are judged, causing reputational damage, and affecting their credibility.

5.6.3 Credibility

As highlighted above, the provision of scientific evidence for policy making impacts the actions of scientists. Many aim to present their research impartially so that their opinions about the environmental cause remain undisclosed. When they are uncertain or unconfident with results they wish to proceed cautiously and not make any claims that could be questioned. There is also a reluctance to provide evidence which may need to change. The reason for these actions, emerging from the interviews, is preservation of their credibility and reputation. This is supported by Oppenheimer *et al.* (2019) who suggest that scientists "believe they must be policy-neutral to be objective and must be objective to be credible".

Another feature of science for policy that could lead to loss of credibility is communication of research which includes 'uncertainty'. This language can be misinterpreted as not knowing, for example, Pyle (12.12.19) stated "when you talk to people, you've got to give them a reasonable assessment of the likelihood of what you're saying, without saying we're very uncertain about this, which sounds like we don't have a clue" and backed up by Warrilow (02.10.20): "when a scientist speaks about uncertainty, he or she knows what they mean and they have a concept in their head...but if they then speak and just say that something is uncertain, the man in the street thinks, 'oh you don't know anything about it then'". Similar responses when presenting uncertainty are also discussed in chapter 6. If an audience believes that the researcher does not know the answer, then they will no longer appear to be a credible expert. This could impact the perceived trustworthiness of their results and increase the level of uncertainty of the audience.

Additionally, it is important to consider if aspects of the research communication might not be interpreted as intended, an example of which was described by Pyle (12.12.19). This related to research reported in a paper by Hossaini *et al.* (2017) on short-lived ODSs not controlled by the Montreal Protocol. The paper describes how these substances are of concern and suggest that without legislative intervention they could delay recovery of the ozone layer. However, the uncertainties associated with this claim were not sufficiently discussed, enabling the media to report that they could have a greater impact on the ozone layer than the paper intended. Pyle admitted that "it's an interesting example of the way science can get used and why scientists have to have a very clear message, and work to try to not be misinterpreted... it was all about the messaging and I think there was certainly a difficulty in communicating the uncertainty”. This shows that unclear communication can lead to misinterpretation, incorrect assumptions about the research, and a misleading message. Again, this highlights the problems of communicating uncertainty and how this can impact on the level of uncertainty of the user, potentially affecting decision-making.

Two aspects of the early days of the ozone depletion story can be related to credibility. One is the Farman *et al.*, (1985) ozone hole paper, which some felt could have been published sooner, however, because the results reported were so unexpected the “author’s careful analysis” gave the paper credibility (Solomon, 2019). The other relates to the results from the first Antarctic field campaign, AAOE, which were withheld to confirm analyses until after the Montreal Protocol was agreed. In the television programme, Saving Planet Earth: Fixing a Hole (2018), Bob Watson[18], states that they “decided to not tell negotiators in Montreal what we’d found because if we’d have been wrong the negotiators would never ever have trusted us again, all we have is our credibility so while we were almost sure what we had in Antarctica, we wanted to be doubly sure”, showing that they wanted to be absolutely certain of the scientific results before reporting their findings to the legislators. The quote also draws attention to the relationship between credibility and interpersonal trust. Credibility provides a means to judge the trustworthiness of the research producer, and therefore providing a way to reduce the level of uncertainty of the research user.

[18] Professor Sir Robert T. Watson FRS, Director of the Science Division and Chief Scientist for the Office of Mission to Planet Earth at the National Aeronautics and Space Administration (NASA) at that time, (see https://tyndall.ac.uk/people/robert-watson/).

Impartiality, vulnerability and credibility become more important when scientific evidence is used for decisions. The following quote from Warrilow (02.10.20) summarises the reason for this: “the world in which politicians operate, they don't operate in the scientific world, they operate in a world where they balance risks automatically in their head, so who do you trust? … as an official you know people who have got a bee in their bonnet and others who are quite level-headed...so actually, something we haven't talked about, this whole issue, ultimately, is about people and their perceptions of other people”. The scientists interviewed have tacit principles that they anticipate will be used by others to judge their research and are reluctant to provide information about their beliefs and values that might jeopardise their credibility. The communication of uncertainty could also impact them negatively if not presented with the audience in mind, leading to misunderstanding. Maintaining credibility is vital. Experts need to be trusted so that their research is seen as trustworthy and can be relied upon for decision-making rather than trusting other conflicting knowledge sources (Barnes, 2005; O’Neill, 2010). Tacit principles are explored in more detail in chapter 7.

5.7 Interviewee reflections: looking backwards and forwards

The challenge of ozone depletion was being tackled at a similar time to the development of the post-normal science concept. However, although ozone depletion would appear to be a post-normal scientific challenge – there were many uncertainties and decisions needed to be made urgently – it can be argued that this phenomenon was essentially normal science that fed into a legislative process. The solution was relatively straightforward (stop releasing CFCs), precautionary legislation was initiated based on hypothesis, and the Montreal Protocol had been signed before full evidence was presented. Uncertainties were not a source of inaction; decisions were made before data became available so there was little need for the research quality to be assessed.

Many of the atmospheric scientists have now moved on to the problem of climate change. However, although both are atmospheric-related problems, there are differences between the two environmental challenges. The problem of ozone depletion is essentially solved, with the Montreal Protocol legislation enabling the ozone layer to slowly regenerate. Ozone depletion is a less complex problem with one main culprit (CFCs) and once removed from production and release the ozone layer could gradually recover. By contrast, for climate change there are many culprits, and the impact of removing/reducing these affects daily lives across society, which is much more controversial. Uncertainties have been used as a reason for inaction, the quality of scientific research has been questioned, and there is extensive input from an extended peer community. Several studies have compared the response to ozone depletion to that for climate change. For example, Ungar (2000) argues that the public understanding of the ozone problem was aided by the use of easily understood 'bridging metaphors' from popular culture (e.g. 'penetration of the sun's rays though a protective shield' resonates with science fiction, such as Star Wars) along with a sense of urgency of risk to human health. Such features haven't been replicated in climate change communication. Grundmann (2006) considers the differences in terms of political will, concluding that leadership by institutions in the USA enabled the legislation for ozone depletion to move forward, which hasn't been the situation for climate change.

The coronavirus pandemic in 2020 provides a contemporary example of the use of precautionary action by Governments, particularly at the start with regard to mandatory restriction of movement and mask wearing in many countries. This was deemed necessary due to the speed of virus transmission around the globe and the number of deaths occurring globally, alongside the many scientific uncertainties. The mandatory restrictions elicited different behavioural reactions due to a variety of reasons, e.g. age, gender, personality, political ideology, culture (Kleitman *et al.*, 2021). In a study conducted with participants from Australia, Canada, USA and the UK, Kleitman *et al.*, (2021) found that in the early days the compliance rate was 90%. Reasons for why people complied included health fears (Goldner Lang, 2023) and institutional trust (Seyd and Bu, 2022), which are similar to the reactions to stratospheric ozone depletion, discussed above. The link to human health risk is much less obvious with climate change.

Looking backwards provides some areas of learning from the ozone story that could be applied to other contemporary environmental challenges, such as alternative ways to communicate potential outcomes. Consideration of the counterfactual and the use of risk to explain the potential impacts, were suggestions that emerged from the interviewees. Looking forwards we can explore how data science is being incorporated into contemporary atmospheric research, discussed as part of the interview questions.

5.7.1 Counterfactuals

One method to look at the alternative consequences of decisions is consideration of the counterfactual – a term to describe what the situation might look like if different or no decisions had been made. The challenge of ozone depletion provides an opportunity to look backwards to assess what the current situation might look like without the positive impact of the Montreal Protocol. This was highlighted by Anon (17.03.21): "leads to the counterfactual because often you can't evaluate, there are very few cases, I think, where you can go back and say 'I can clearly show the impact of this policy'". The importance of this is summarised by Harris (22.04.20): "[ozone] recovery is important, because it is the Montreal Protocol doing what it's meant to...if we got it wrong with ozone, it would really reduce the confidence in what we're doing with climate...recovery is to show that what was done for ozone was broadly right, not completely right...so you can trust us". Therefore, by considering the counterfactual for ozone it is possible to evaluate the reliability of the research used in the assessment reports to make decisions, to indicate that the scientists are credible and that their future climate-related research is trustworthy, despite the uncertainties.

Warrilow (02.10.20) suggested using consideration of the counterfactual to show an alternative scenario to decision-makers: "when you're trying to give politicians a sense of the counterfactual because that's what you're trying to do, you're going to see what happens if we don't do anything" going on to say "something very important here that I learned is that when you're trying to give politicians a sense of the counterfactual…it's best to make it as simple as possible…it's a sense of what the scale of the problem is and I think the people don't quite often present this in the right way to politicians, who are quite sensible, they know that if you keep doing the wrong thing for long enough, you will run into problems, and that's all you need to show them, you don't need to be very complicated about it". This highlights that by providing a counterfactual argument decision-makers can see what is likely to be the outcome, or the risks of inaction. The quote also draws attention to simplicity as key to communicating with policymakers. For example, the IPCC provides 'business as usual' scenarios in the Policymakers Summary to provide an indication of what could happen to global temperatures if no action is taken (Calvin *et al.*, 2023).

Consideration of both uses of the term 'counterfactual' described above could be applied to contemporary environmental research to provide an indication of alternative outcomes. Additionally, the use of the counterfactual could provide an additional layer to post-normal science to incorporate the reflective element after a decision has been made when adaptation is required (see Figure 18). This would provide additional review and transparency and promote trust in the experts that the scientific research was effective in aiding decisions, despite any uncertainties.

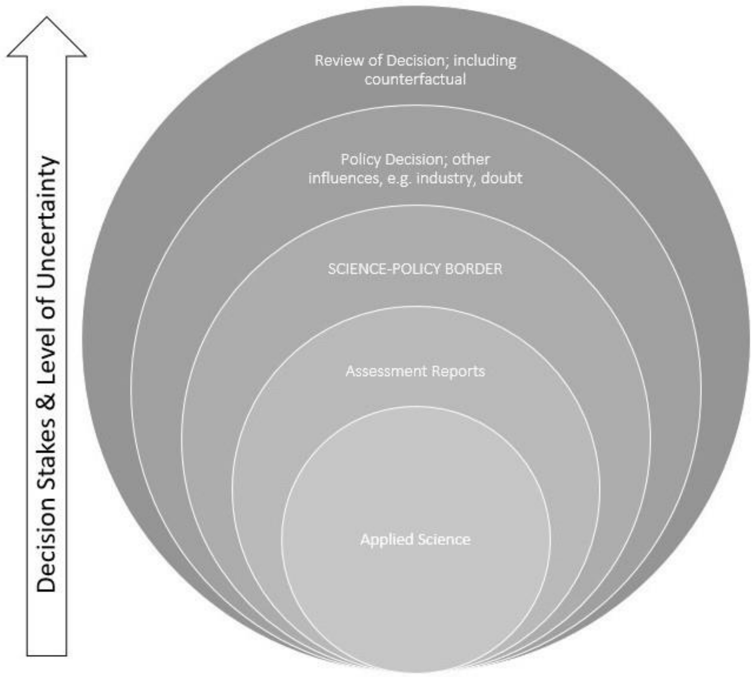

Figure 18. The position of the science-policy boundary, additional influences on decisions, and consideration of the counterfactual

Figure 18 shows how the requirements of science have developed for this ozone depletion challenge. They move from applied science to the boundary where science meets policy needs and beyond to incorporate the other influences upon policy decisions and inclusion of decision reviews and adaptation if further mitigation is required. These features are also relevant to contemporary environmental challenges and post-normal science.

5.7.2 Risk

The use of risk for communicating information on potential impacts to non-experts was discussed by Harris and Warrilow. The relationship between uncertainty and risk was discussed in chapter 2. As Warrilow (02.10.20) states: "uncertainty for most people is just a sideshow, or a tool to be abused or misused as they see fit" so by discussing risk instead of uncertainty people would gain a better understanding of an environmental challenge, and more specifically how it affects them. Using risk translates the uncertainty into a more meaningful and imaginable mode of communication – "uncertainty on its own only tells part of the story, you've actually got to combine it with the risk in policy terms to decide, well, risk inherently includes uncertainty anyway, so it's uncertainty and its impact" (Warrilow, 02.10.20) and "I think it's, so it's more showing what's the context that risk or uncertainty is interpreted within also matters" (Harris, 22.04.20). Warrilow (02.10.20) goes on to conclude that "the big task for the scientific community is to explain risk better". This was also a conclusion of Sutton (2019) who suggests using risk to communicate uncertainty as a way to engage people with climate change and contributing a lack of this to the lack of integration between IPCC working groups. The problem with this is that the risks are probably different for each stakeholder. As Warrilow (02.10.20) points out: "in any public policy that requires change there's always winners and losers…clearly the people negatively affected will push against the change…but I think in the communication of science it's important to show what the benefits and disbenefits might be to different communities. I think perhaps it's quite important, but probably quite a bit of uncertainty in that". Confirming that risk provides a useful means to discuss these consequences, but people's behavioural response to these is very unpredictable, or uncertain. As mentioned in chapter 2, people's appetite for risk varies, impacting decisions, and the reaction to those decisions.

One potential winner is industry if they are prepared to take a risk and invest in new technology. Warrilow and Pyle conclude that ultimately it will be industry that brings about action on climate change. Warrilow (02.10.20) stated: “throwing more science into it doesn't change the game very much now because it's all there, it's been there for quite some time. What really needs to happen I think, well, I think what actually changes the game now is when others come in and see that we can do things better and make money out of it. That's what will change the equation. I'm sorry, it sounds very cynical, but I'm afraid that's – the ozone layer story is exactly that, once the industry saw that they could continue making chemicals, but of a different sort and make more money, actually, then problem gone really”. Pyle (12.12.19) also concludes: “if I was an industrialist, I would be trying to think, how can I make money out of this? You know, ‘what am I going to be doing that will allow me to have an advantage, we can sell technologies, for example, all around the world if we come up with really clever technologies’”. This argument relies upon industries to take risks and invest in development of the new technologies. If new climate change mitigating technologies are developed and adopted, previous polluting technologies would gradually become obsolete, removing the ability of individuals to use environmentally harmful products.

5.7.3 Data science

Returning to contemporary scientific practices, Wild (17.03.20) described the changing nature of atmospheric modelling, how data science and statistical techniques are being incorporated and how these are making atmospheric researchers think differently about uncertainty. The incorporation of data science methods is an innovation for atmospheric research, as Wild (17.03.20) states: “we're playing catch up…there are many disciplines…that are way ahead that we can learn lots from”. Now that understanding of the atmospheric processes has been addressed, research has turned to smaller scale issues where the uncertainties are more evident, creating a “greater interest in data science and uncertainty...applying slightly simpler learning rather than increasing complexity all the time...trying to think about taking the models we've got and understanding...what the sources of uncertainty are" (Wild, 17.03.20). Previously uncertainties in data have been less concerning to the atmospheric community as the scientists have been working to understand the chemical and dynamical processes in the atmosphere. Wild (17.03.20) also discussed how the "new data science type approaches coming along, the statistical models, … do a much better job of prediction .. because that's what they're designed to do, but not necessarily understanding". However, once it is accepted that the physical processes are broadly understood then it is the prediction aspect which is more useful for decision-making. For example, data science techniques could be used to provide evidence for predicting risks, as Warrilow (02.10.20) mentioned: "actually it's very hard to compare the risk unless you know what the numbers are". Therefore, statistical uncertainties can be used to communicate a quantitative estimate of risk based on available data, and can aid decision-making. The following chapter investigates data science and statistical uncertainty in more detail.

5.8 Conclusion

Over the past half-century, the depletion of the Earth's protective ozone layer due to human-made chemicals has been a major global environmental challenge characterised by scientific uncertainties, varying opinions, and conflicting narratives about the sources of ozone destruction. Despite these uncertainties and challenges, global policies were agreed and continue to evolve, and the ozone layer is showing signs of recovery.

This case study has reviewed the uncertainties and decision processes to explore how uncertainty was navigated for this environmental problem. The chapter has contributed decision-making insights to the data-to-decision pathway, linking scientific research to policy decisions. In this story scientific uncertainties were not seen as problematic for the decision process, with the precautionary principle driving legislative action. Acknowledgement of the scientific uncertainties was incorporated into the Montreal Protocol with provision to reassess scientific research every four years. Scientific assessments are an established method to reduce uncertainties about environmental challenges, by providing a consensus of experts, and are used by decision-makers for various environmental challenges. However, getting to a consensus is not easy, experts do not always agree and some wish to promote their own research. The methods for producing these reports have developed over the years with more management, steering committees, and chapter lead-authors. The use of these assessments also highlights that due to uncertainties decision-making should not be viewed as a final step but rather an ongoing process, requiring continuous research and evaluation.

Figure 19 summarises the communication and decision uncertainties identified by the interviewees in this chapter, which are added to the uncertainty typology in chapter 8.

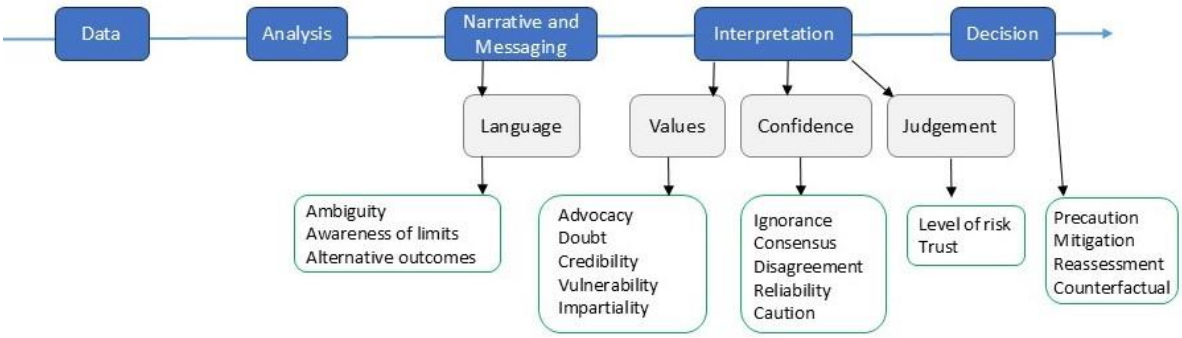

Figure 19. Summary of uncertainties feeding into the uncertainty typology discussed by interview participants

The key findings from this chapter are:

- When policy action is required, scientists are pushed out of their academic norms, which creates an uneasy relationship between science and policy. The chapter has provided insights into the actions of scientists involved with a specific historical environmental challenge which required science to work with policy. This study argues that many scientists are reluctant to blur the lines between science and policy, they wish to remain impartial so that they cannot be accused of adding any political bias to their scientific messaging. In doing so, they avoid becoming vulnerable to criticism and are able to maintain their credibility. By maintaining credibility the scientists are trusted, their science perceived as trustworthy and their research can therefore have impact on future related environmental challenges, i.e. evidence they provide on climate change can have an impact. By placing their trust in the scientists, the research users can reduce their level of uncertainty in the research outputs and judge their level of risk, so that decisions can be made.

- The level of uncertainty of the scientist affects their confidence for communication of evidence. For example, the more uncertain they are, the less confidence they have in their research and are more cautious with their communication.
- The communication of uncertainty was a concern for interviewees in this study. The valuable experience they have gained highlighted two ways to communicate uncertainty so that it is impactful on decisions. These suggestions offer alternative ways to portray uncertainty which can be incorporated into the communication of contemporary environmental problems. One proposal is the importance of translating uncertainty into risk so that potential environmental impacts are apparent, and more relatable. Statistical uncertainty is being used to show the probability of events, and hence the risk of occurrence in a particular location, which can engage stakeholders in more informed decision-making. As there is always a counterfactual, the other way to communicate uncertainty is to highlight this to decision-makers, so that they can be made aware of the alternative outcomes if different decisions were made. These two methods are incorporated into the framework for uncertainty communication developed in chapter 8.

This chapter has identified from interviewees that data science techniques are becoming incorporated into contemporary atmospheric research. The importance of statistical uncertainty along with the increasing importance of data science methods requires a more in-depth exploration, so the following chapter looks at these in more detail.

6 Challenges of environmental data science

6.1 Introduction

The increasing importance and incorporation of data science methods to environmental problems has been emphasised in previous chapters. However, there are some aspects of environmental data science that can create tensions and challenges for those working in this cross-disciplinary research area. Drawing on evidence from a focus group study with researchers working on a collaborative environmental data science project, DSNE, this chapter explores types of uncertainty, and sources of tension, experienced by environmental data scientists who have a statistical or quantitative methods background.

Statistical uncertainty is a key feature of data science, with a specific and narrower definition of uncertainty understood by those working in this domain. Thus, this chapter contributes to exploring the 'statistical theory' aspect of environmental data science uncertainties highlighted in chapter 3. This specific understanding of uncertainty is a source of misunderstanding to non-disciplinary stakeholders which causes frustration to statisticians. An underlying assumption of this thesis is that uncertainty is important, and hence that it needs to be navigated by stakeholders. Therefore, one question the focus groups were asked specifically was whether they think it is important, and their thoughts are included in section 6.6.1.

Alongside this, the challenges of cross-disciplinary research in this context are explored in detail. This considers the differing underlying philosophies of the researchers, along with problems of language and communication. As will be shown in this chapter, the increasing use of Bayesian statistical methods introduces a more subjective philosophy into environmental data science, whereas environmental scientists retain a realist philosophy. However, due to the complex and uncontrollable nature of environmental studies researchers are aware of being pragmatic about what they can achieve, while searching for the truth.

6.2 Summary of method

Following the uncertainty literature review it was realised that a deeper investigation of uncertainties in environmental data science was required, particularly to understand the types of uncertainty associated with using statistical methods. This exploration contributes to answering the research questions about the types of uncertainty experienced by environmental data scientists, and the techniques used to handle these. To explore this aspect of uncertainty and aid understanding, three focus groups were held with members of the Data Science for the Natural Environment project (DSNE, based at Lancaster University) in July 2021. This enabled the author to observe how an interdisciplinary group of data scientists discuss uncertainty between themselves, without being led with specific questions from an interviewer. Also emerging from these discussions are some sources of tension which can occur in environmental data science.

The DSNE project provided access to methods-focussed researchers working on developing data science techniques to look at the environmental challenges of ice sheet melt prediction, air quality modelling and land use changes. An email invitation to participate was circulated to all those involved with the project. Thirteen participants took part in the study, with each group consisting of four or five academics, whose main specialist area is statistics or environmental science. Ethics approval for the study was obtained and is available in Appendix A, and the participants were guaranteed anonymity. The groups were conducted on-line, recorded, and transcribed by the author/moderator. Each focus group transcript was analysed individually, and sections of interest were highlighted. Quotes from each focus group were then amalgamated and thematically analysed. The themes developed include the philosophies of environmental data scientists, their perspectives on uncertainty, the uncertainties they encounter, and communication of uncertainty, which are discussed as sections in this chapter. Further details for the thematic analysis are provided in Appendix J.

The focus groups were voluntary, and people were able to sign up to any of the three dates offered depending on their availability, so the groups were randomly self-selecting. Each group had a different proportion of subject specialists and academic levels (summarised in Table 9), leading to different discussion topics within each focus group. Most of the discussion came from members of the groups, although the focus group moderator occasionally asked questions to aid the flow of conversation (see 0). Some of the themes evolved from these questions put to the groups by the moderator and these are acknowledged in the relevant sections. Focus Group 1 discussed uncertainty from a statistical viewpoint; Focus Group 2 discussed the uncertainties associated with process and scenario models; and Focus Group 3 had a wide-ranging discussion from differences between frequentist and Bayesian statistics, language ambiguities and behavioural uncertainties.

Table 9. Summary of the specialist areas and academic level of the participants

Focus Group	Participant	Academic Level	Specialist area
Focus Group 1 1 July 2021	FG1-P1	Postdoctoral	Environmental Science
	FG1-P2	PhD researcher	Statistics
	FG1-P3	PhD researcher	Statistics
	FG1-P4	Academic	Statistics
	FG1-P5	Postdoctoral	Statistics
Focus Group 2 8 July 2021	FG2-P1	PhD researcher	Environmental Science
	FG2-P2	Academic	Environmental Science
	FG2-P3	Postdoctoral	Environmental Science
	FG2-P4	Academic	Statistics
Focus Group 3 15 July 2021	FG3-P1	PhD researcher	Environmental Science
	FG3-P2	Postdoctoral	Statistics
	FG3-P3	Postdoctoral	Statistics
	FG3-P4	Academic	Environmental Science

6.3 Philosophies of environmental data science

A topic of discussion in two of the focus groups was the underlying philosophies of environmental data scientists. As mentioned in chapter 3, Bayesian statistical methods are more suited to environmental data because within an environmental context it is not possible to carry out multiple tests (“there's one planet and it's got one data set”, FG1-P1) making the frequentist methods less suitable (Aguirre *et al.*, 2013). However, statistical methods are underpinned by different philosophies, so a statistician’s perspective of research will depend on whether they follow a classic (or frequentist) or Bayesian approach. Alongside these statistical philosophies, the pragmatic realism approach followed by many environmental data scientists was also discussed.

6.3.1 Frequentist vs Bayesian statistics

The differences between frequentist and Bayesian methods cropped up in the discussion in both Focus Groups 1 and 3. Focus Group 1 went into more detail, with (FG1-P4) confirming that “Bayesian is a way of thinking” emphasising the philosophical aspect of using these methods. Focus Group 1 discussed the benefits of using a Bayesian approach: “one of the strengths I see of the Bayesian approach is that it's very explicit about having a set of prior assumptions, and then it's very clear about how you update those in response to new information, and then you generate further assumptions and you can kind of iterate on that process” (FG1-P1); and: “I see it as a more principled way to understand the uncertainty falling at the other end but at least you're open and up front about the choices that you're making and in choosing this model” (FG1-P4). Both these quotes show that the participants approve of the transparency and openness of the information and assumptions being incorporated into their research by using Bayesian methods.

Although the statisticians in Focus Group 1 follow a Bayesian philosophy ultimately it was felt that the differences weren’t particularly relevant to anyone outside statistics and using either methodology would probably provide a similar result – “the credibility intervals from the Bayesian world are essentially the confidence intervals of frequentist in almost all situations...and so yeah, I just don't think it really has a great deal of influence on the final outcomes" (FG1-P4). However, it is the different philosophies that underlie these methods which provide insight into the perspective of the researcher, and which created a source of tension within the discipline of statistics between the 1970s and 1990s (FG1-P4). FG1-P4 discussed how traditionally statistics tried to provide an objective representation of data, stating: "their philosophy was you should include none of your own beliefs into the influence, you should let the data give you the answer". As an advocate of Bayesian methodology, FG1-P4 went on to describe this as "complete rubbish...we choose how you're going to look at the data and so your prior understanding of the process affects the kind of answers you get", with "the gymnastics and tricks you use in the frequentist world are basically just hiding the fact that people are being Bayesian" (FG1-P4). This highlights that even when producing a seemingly objective statistical assessment of data it's not possible to remove subjectivity from the data analysis, but some people are reluctant to acknowledge this.

One participant in Focus Group 3 described uncertainly as representing truth: "when we talk about uncertainty, we presume there's a truth" (FG3-P2), although recognising that this is not an absolute truth, going on to say "in the forecast there will be a truth and then uncertainty is to acknowledge that the way we represent or describe it, we're not exactly sure what that is, it gives some range or kind of wiggle room". A belief that data will provide the 'truth' represents the positivist mindset associated with natural scientists (see chapter 4), although acknowledging that they have some 'wiggle' room suggests that they are pragmatic about what they are able to achieve.

6.3.2 Pragmatic truth

Many participants in the focus groups are aware of the limitations of their analyses, particularly the environmental modellers, stating for example: "your models are never going to be perfect because they're a model of the environment and you need to know that" (FG2-P3): "I always [say] there's always a model...I guess there's, so there's a pragmatic truth that we might be after" (FG3-P4) and: "at the end of the day, you're trying to represent a real-world situation, but you're only going to be one possible simulation of what that real world outcome can be" (FG2-P2). Recognition of the limitations of the data and tools available is necessary to carry out research, as described by FG1-P3: “you don't know the truth, so you always have to take some sort of level of assumptions in order to simplify whatever it is you're trying to model to a point that it is actually computable”. The quest for scientific ‘truth’ is not easy, nor realistic, especially within the complexity and unknowns of environmental science. Therefore, it has been suggested that to pursue their research many environmental data scientists subscribe to the philosophy of critical realism, described in chapter 4, thereby remaining positivist but pragmatic about what they can achieve.

Some researchers in the groups grapple with the friction between the scientific method and their beliefs. They are conscious of the biases that they could be adding, described by FG3-P4: “how we bring certain biases and ways into how we do things, for example ... climate models, they're all supposed to be predicting the same thing, they’ve all been given the same inputs, yet they give a whole range of different outputs...the decisions you make in the framework that you build...that decides which model is better is going to be imperfect itself...and that uncertainty is extremely difficult to quantify”. They conclude that “this sprawling uncertainty monster is difficult” (FG3-P4). This dilemma was echoed by FG2-P4 who stated: “human decisions are still there in all the things about the parameters, things where Bayes did fantastic work for uncertainty, but there are all the things behind for which is often conflicting with your human persona”. These quotes indicate that the researchers feel that they should provide a quantification of the uncertainty in their models and are conscious that they are unable to do this. It could be argued, however, that being aware of their input and biases is positive, it can help reduce some areas of uncertainty by its acknowledgment and can provide transparency.

Encompassing a pragmatic mindset enables the environmental data scientists to be “comfortable” with the existence of uncertainty (FG3-P1 and FG3-P4), and it does not hamper their research or communication of it: “I don't want to sweep [uncertainty] under the carpet” (FG3-P4). This participant goes on to explain, “we don't really deal in proof, we're dealing with degrees of uncertainty and we have to get comfortable with that” (FG3-P4). An additional element of pragmatism is the recognition that research could provide a ‘truth’, until someone else uses a different method and finds another 'truth' or alternative result: "the humble thing is to admit that knowledge itself is contingent and someone else will come along later and come up with a different way of doing it" (FG3-P4). With many contemporary environmental problems it is hard to know what the 'truth' is as these are subject to unknown future changes, so the creation of several possible future scenarios is the best option for making decisions. However, as these scenarios are based on assumptions, experts may disagree, which will affect the level of uncertainty of the decision-maker.

A pragmatic attitude becomes more important when scientific results feed into global decision-making. It becomes necessary to recognise that there are other political considerations that override the use of the best possible science. For example, a participant in Focus Group 3 described a dilemma that had arisen from their involvement as a lead chapter author for an international report regarding the use of lower quality research. An analysis had been produced by researchers who were from a nation where the research infrastructure was less developed. The initial reaction of the participant, particularly when considering uncertainty, is that the analysis should not be included, however, the consequences of this needed to be considered, especially for promotion of diversity of research. For example: "it gets political, small 'p', if you start saying actually you know we have measurement X, might not be so good, then that's going to maybe endanger someone's funding" (FG3-P4). If their work is not seen to be internationally relevant then the researchers funding could be reduced, so their research infrastructure will remain undeveloped or even disappear. This reduces the global diversity of research and potentially research capacity in regions that could be adversely affected by global environmental problems.

It is clear from this section that the philosophy of the environmental data scientist affects their research, but this philosophy varies between individuals and disciplinary backgrounds. The increasing use of Bayesian methods shows that data scientists are becoming more realistic about their subjectivity in the research process, and although some scientists strive for objectivity (realism) the nature of complex environmental problems requires them to be pragmatic about what they can achieve. Ultimately, these different philosophies affect the ways that stakeholders navigate uncertainty, creating a source of tension in cross-disciplinary research groups, which requires a means of reconciliation for the research collaborations to succeed.

6.4 Perspectives of uncertainty

The moderator started the focus group discussions by asking the participants what uncertainty meant to them in their research, enabling exploration of the different perspectives of uncertainty of the environmental data scientists, a fundamental aim of this thesis. The differing background specialisms, and different compositions of subject specialisms, between participants in the individual focus groups led to diverse conversations about what uncertainty meant to them. The following subsections are divided by disciplinary area to reflect these differences emerging from the conversations.

6.4.1 Uncertainty in statistics

Statistical uncertainty in environmental data science, introduced in chapter 3, provides a way to quantify and acknowledge the uncertainty and complexity of environmental data. Statisticians, who were interviewed as part of the CEEDS study (discussed in the following chapter), described statistical uncertainty as a way of "mopping up that additional complexity that we can't understand" (CEEDS interviewee P4) and: "a lot of the data we collect...can be messy...you can't control everything out there in the environment, so we have to account for these things" (CEEDS interviewee P5). Returning to the focus group discussions, uncertainty was described more quantitatively: "so for me it's very much about error bars and confidence" (FG3-P4): "we don't have perfect information...so we try and quantify where we don't know any information" (FG1-P3) and "as a statistician we all just kind of quantify that [knowns/unknowns etc - referring to Rumsfeld's quote] as a distribution of things" (FG1-P4). FG1-P4 described that when they are thinking about uncertainty, they: "build a probabilistic model of where things are coming from and then think about the uncertainty in terms of that". FG1-P4 confirms that quantification of the data provides information on uncertainty that can then be used within a decision-making context: "what I do is try to quantify and process and use uncertainty for benefit...particularly around how uncertainty should be handled in a decision-making scenario and can you make use of that uncertainty to decide what to do next". The quantification of uncertainty using statistical methods provides information on the probability of a particular event occurring, enabling decision-makers to consider the risks of a particular action.

Delving deeper into the meaning of uncertainty, several participants described that to them uncertainty relates to variability, for example: "uncertainty is trying to quantify the unknown variation" (FG3-P3): "when someone talks about uncertainty, I immediately think about variability of a random variable" (FG1-P5) and, following further discussion in Focus Group 1: "I think that's a really, really strong point in the way that intuitively so many of us think about variability" (FG1-P1).[19] The statistical response to this variability is quantification using error bars or confidence and credibility intervals, which provide a range within which a result falls. Statisticians use a range of tools to analyse data and don't distinguish between aleatory and epistemic types of uncertainty (discussed in chapter 3), as FG1-P5 stated: "I'm thinking about the variability and probability distribution of that variable of interest, that can be, an observed variable, that can be a latent variable, that can be a predictor, that can be estimator, because all of them at the end of the day are random variables", so labelling the distinction between these natures of uncertainty appears not to be relevant for environmental statistics in practice.

As discussed in chapter 3, uncertainty is often viewed negatively. However, statisticians in the focus groups do not see uncertainty as a problem – "the word uncertainty has negative connotations…I think it's better to see as an extra layer of information that you can get from describing your results with uncertainty attached, that's very important" (FG3-P2) and "uncertainty is something positive and good to measure and good to have lots of thoughts about rather than something that you're supposed to be, 'Oh, there's an uncertainty that's bad'" (FG1-P1). To statisticians, uncertainty presents an enjoyable

[19] Variability is defined as the inevitable differences that occur between measurements or observations, some of which may be explained by known factors, and the remainder attributed to random noise (aleatory) (Spiegelhalter, 2019)

challenge, it provides a source of curiosity and a reason for their research, encapsulated by FG1-P1: “if you're a statistician, the uncertainty is like it's kind of everything you're interested in”. Elaborated by FG1-P4 who stated: “it helps us understand where we need to, where we should try and understand more” and to FG1-P3 a need to “drill down into that a bit and what that actually means”, showing that statistical uncertainty provides additional information about data, and an indication of areas that need further study.

The understanding of uncertainty in statistics is quite specific, it provides a means to quantify the inexactness of data. FG1-P4 concludes that: “we're very narrow in the kind of uncertainty we tend to consider in stats” and goes on to say that “it's very hard to discuss widely with people because everybody means something else... I've had endless arguments with economists and psychologists about all sorts of different kinds of uncertainty... I usually find out we’re talking about different things”. This distinct view of uncertainty by statisticians provides a distinct definition of uncertainty, which can obviously lead to misunderstanding when discussing uncertainty with other disciplines, which have a different perspective.

6.4.2 Uncertainty in environmental science

The problem for environmental data science is that research that only provides a statistical analysis of uncertainty does not always tell the whole story – it provides a quantification on the variability of data but not any information about why this is occurring. Therefore, once environmental scientists became involved in the focus groups’ conversation, discussion about uncertainty changed to include other perspectives, especially consideration of the sources of the uncertainty. These sources are not considered important in statistics, as described by FG1-P4: “there's whole disciplines outside of stats that we never really come across that really care about different types of uncertainty and where it’s coming from”. A reason for this is suggested by FG1-P1: “classical ideas of uncertainty probably relate to more classical ideas of science as something where you can control things, you can repeat an experiment, you can control all of the variables that go into that experiment, and then you can talk about uncertainty in the outputs because you know what you have varied in the inputs”. This quote highlights that when an experiment is controlled there are no additional sources of uncertainty to influence the research. This is not the case in environmental science, emphasising the difference between ‘normal’ science and science relating to environmental phenomena, where control over the sources of uncertainty is not possible.

As mentioned above, once research crosses the statistics/environmental science boundary environmental scientists want to know where the uncertainty is coming from. FG1-P5 described how the sources of statistical uncertainty can be split up: “uncertainty can be divided by sources...so for example, we call some uncertainty, ‘explainable uncertainty’ because in some way within that we can explain that by some predictors and there is another uncertainty that we call ‘unexplainable uncertainty’ because we know that there is some spatial structure or a temporal structure that we don't know what the reason for that is”. Providing an explanation for the uncertainty is important, FG1-P3 describes that when uncertainty is presented without any details: “it's just a kind of acknowledgement that it's imperfect information, but you don't know what the source of it is”. The importance of source is also emphasised by this quote from FG1-P1:

> *“for me when someone says uncertainty it immediately raises questions of what's the uncertainty in...feels pretty meaningless to me until someone's told me what the drivers of that uncertainty are...like time series which have uncertainties around them, but you could never think of those as actually this is the real potential range of distributions of that time series, 'cause you know that that uncertainty is way too narrow for the techniques that are involved, and it's because the uncertainty is generated from the internal uncertainty of a model, but it doesn't really account for how uncertain the physical processes being represented by that model are or the uncertainties in the datasets”.*

Uncertainties within process models (mentioned in the quote above) was a common subject emerging from all the focus groups. Focus Group 2 included a majority of environmental modellers, so their reflections focused mainly on the sources of uncertainties within different types of environmental models, such as climate models, land-use models and models to create scenarios. For example, FG2-P1 was concerned about the uncertainties of model complexity: “climate models...they are getting more and more complex, it becomes harder and harder to properly understand the uncertainties...and the more complex your model is, the harder it is to sort of represent all of these different sources and their importance”, and also referring to models FG2-P4 mentioned the “sources of uncertainty which are very difficult to find”. Without details about the uncertainty source it is not possible to know whether it can be reduced, or whether any additional details useful to inform decisions need to be incorporated. Additionally, understanding the sources of the uncertainty can also influence the level of uncertainty or confidence that an individual stakeholder feels about research results, potentially affecting the decisions they make.

6.5 Sources of uncertainty

Statistical uncertainty provides information on the variability of data, however, consideration of why this uncertainty is occurring is also necessary. It is important to understand the sources of uncertainty, especially when deciding how it can be handled, and how the uncertainty is subsequently communicated. The following subsections look in more detail at some sources of uncertainty discussed by the focus groups and raised in the previous section.

6.5.1 Assumptions

Assumptions were discussed or mentioned in all the Focus Groups but most in depth by Focus Group 1. As mentioned in section 6.3.1, prior assumptions are a fundamental feature of Bayesian statistics. As mentioned in chapter 2, they are also a feature of environmental science to enable research to continue instead of becoming impeded by uncertainties: “I think that we do tend to make a lot of assumptions in environmental science about the factors which are going to be significant for any kind of outcome that we're looking at” (FG1-P1). The need to make assumptions is vital to environmental statistics, with FG1-P3 stating: “I guess the assumptions...allow you to model the process in the first place, like if you don't make the assumptions then you...can't really go anywhere". The advantage of using a Bayesian statistical approach provides the ability to incorporate assumptions into an analysis “as long as those assumptions are testable and verifiable to a certain level, then you’re kind of fine to proceed from that basis you've got some of your sources of uncertainty sort of laid out for you in a sense” (FG1-P3). Acknowledging assumptions provides a level of transparency about the sources of uncertainty incorporated into the calculations.

Focus Group 1 agreed that assumptions are generally based on experience: “there are assumptions even before you start being able to calculate an uncertainty you are making assumptions about the things which drive that uncertainty, which are kind of either experience based, or process knowledge based” (FG1-P1). However, it was acknowledged that this could introduce another source of uncertainty: “you're kind of starting to generate your uncertainties from things which don't actually relate to the real uncertainties, they relate to external knowledge that you have about the situation” (FG1-P1). The uncertainty associated with deciding assumptions was a source of internal conflict for FG2-P4: “the times that we really test our assumptions or why I did that model apart from because I was trained on that model is quite conflicting because once you decide on the model, you're bringing all the possible uncertainty on that”. This highlights that although the assumptions enable the research to progress, they can also be a source of uncertainty. Moreover, it also raises the question of people’s differing experiences, so an additional source of uncertainty could be created as the researchers may not necessarily agree on what has been assumed.

In some instances assumptions are documented, however, within statistics FG1-P5 mentioned that the assumptions aren’t usually stated explicitly in papers, although it is usually possible to understand the assumptions that the author has made. Focus group 2 discussed the use of virtual research environments (virtual labs) and the advantages they provide with regard to assumptions: “I think the labs help that because you can view the assumptions made at each step” (FG2-P3). This developing research tool provides a means of transparency so that all collaborators can see the assumptions and decisions that have been made. When working in a transdisciplinary way, discussing and agreeing assumptions so they are transparent aids the research process, as described by

(FG2-P2) : “most progress we've made is through transparency...working in a more codesign way with your user…so you communicate all of the assumptions you're making along the way, when they’re unsure of an assumption you know you’ve got do some sensitivity or uncertainty analysis around it, but actually when they’re kind of fairly confident that it meets their needs then it's an uncertainty you don't really need to worry about it”. Transparency of the research processes has arisen throughout the focus groups as an important part of the environmental data science research process. It provides a way to reduce and overcome some uncertainties for different stakeholders and enables decisions to progress.

6.5.2 Environmental models

There are multiple sources of uncertainty within models, as discussed in chapter 3, summarised by FG2-P2: “you've got uncertainties in the data, you've got uncertainties in the scenarios, how those scenarios are parameterised in the individual models and in how the models are coupled together”. The lack of examination of these different aspects was raised as an area of concern to participants in section 6.4.2. Some participants noted specifically the quality of data used in environmental models, which is not always accounted for when results are presented. For example, regarding data input, FG2-P3 discussed their experience of looking at data uncertainty in models and found that “a lot of people treat their data as verbatim, when actually there's uncertainty in the data”, and FG3-P1 stated that there is a need for “interrogating where your data is coming from, so what's the original source?”. Additionally, if these different sources of uncertainty are not scrutinised then they can compound through the modelling process. Therefore, raising awareness of these sources through the uncertainty typology developed by this thesis could help to reduce model related uncertainty. Another way of reducing the compounding uncertainty is through quantifying its impact at each stage of the modelling process.

Quantification of uncertainty in environmental models is not an established method and thus can be a source of tension in environmental data science between environmental scientists and data scientists. In addition to uncertainty in model input data, uncertainty arises from the structure of models, which the groups discussed in detail. Participants were concerned about the use of models, e.g.: “people forget that different structures of models produce really different outcomes” (FG2-P2). FG1-P1 provides an explanation for this: “people tend to be content with generating uncertainties from process-based models by perturbing things within that model. But that doesn't give you any uncertainty of the model design which I think is probably the biggest factor”. As suggested by FG2-P1 “the goal is - of a model or a more complex model is to reduce uncertainty, but it should probably be to better quantify uncertainty or more accurately quantify uncertainty so that leads to greater uncertainties on your predictions”. FG1-P1 reflected on their experience of conducting research using environmental process models prior to joining the DSNE project, and stated: “dealing with uncertainty was firstly not very precise and secondly it kind of came down to, well, if we credibly perturb our various inputs which could be parameters to models...how is the output that you get perturbed as a result of that? Essentially you would say that you've got a well-managed uncertainty, i.e., your model is doing something sensible” (FG1-P1). The experiences described by FG1-P1 indicate that the attitude of environmental scientists who use process models is to not really consider all possible sources of uncertainty in their model. FG1-P1 goes on to suggest that the “biggest way to better constrain uncertainties in the environmental science world probably comes down to getting them to think about sources of uncertainty properly, and probably most critically getting people not to trust process-based models too much”. Their personal attitude has changed with being part of the DSNE team and they now incorporate data science ideology and a greater consideration of uncertainty to their research. This is a positive example of how culture differences can be overcome when people are prepared to work together across disciplines.

6.5.3 Language

All the focus groups were asked about language uncertainty by the moderator, with two different aspects of language emerging from the discussions. One, which featured in Focus Groups 2 and 3, was the different interpretation of words depending on research discipline: “niche words that you use within your research context that don't translate across to other people” (FG3-P1) and “if you're going to try...and collaborate the biggest barrier to that is misunderstandings around terminology” (FG2-P2). Language uncertainties were discussed earlier in chapter 3 and they add an additional source of uncertainty and challenge for cross-disciplinary research. FG3-P4 summarises this as “ambiguity, I guess would be the sort of formal word when talking about the uncertainty in that [sense]”. Focus Group 3 discussed specific ambiguous words they have experienced, such as recovery, resilience, calibration, validation, which are commonly used in some disciplines of science but have a different meaning outside of those disciplines.

The other feature of language, discussed mainly in Focus Group 1, was about how quantified uncertainty is communicated, with FG1-P4 stating: “lots of people who are trying to deal with uncertainty don't have a language to precisely describe it and work with it” although then going on to say “people who are very used to working with uncertain quantities have generally developed a language to be able to describe what's going on, you see it in lots of the Civil Service reports they've recently, like in last 5-10 years, developed an internal language for reporting stuff...each paragraph has a confidence level attached to – it’s brilliant communication…there’s an official translation between those things and probabilities...once that language of communicating uncertainty is there, we can work with it much better” (FG1-P4). It was also mentioned in Focus Group 2, with FG2-P2 stating that “terminology around uncertainty that lots of people might slightly interpret it in different ways because again...how you address it to do the science is probably quite different to how you will communicate it to a decision-maker... so there's these two different language challenges I think to overcome". One method of doing this for statistical uncertainty was suggested by FG1-P1: “you might change the way that you describe uncertainty is going from talking about confidence intervals and standard deviations and things like that to just talking more explicitly in terms of the value is expected to be within, between X and Y”. These quotes lead to the conclusion that the communication of statistical uncertainty to those who have a quantitative background is more straightforward, as they have a shared understanding of the language. Some focus group participants had experienced misinterpretation of their research results, so the communication of uncertainty was an area of concern.

Therefore, it is necessary to consider the different audience requirements and backgrounds, and tailor the language accordingly, i.e. by the use of less technical wording.

6.6 Communicating uncertainty

Once the environmental data scientists move away from the comfort of their normal science into providing results for decision-making, they are less sure of how to proceed. The main dilemma that emerged in all the groups was communication of quantified uncertainty, and its interpretation. This ranged from, getting people to understand uncertainty so it wasn't interpreted as ignorance, how to provide realistic expectations, and knowing what an audience needed to know. However, overarching these problems is the consideration of whether it is actually important to communicate uncertainty.

6.6.1 The importance of uncertainty

The focus groups were questioned by the moderator about whether they thought uncertainty was important. In section 6.4.1 it was noted by several participants that looking at uncertainties are part of the appeal for a scientific researcher: “I think some of the work on uncertainty we do for scientific interest, and we get a nice paper out of it” (FG2-P2). However, posing the question about whether it was important got the focus groups to discuss their thoughts about whether it was a necessary part of their research. The consensus across all the groups was that quantified uncertainty is important, for example, it is “obviously important because your results don't mean that much without some form of uncertainty around it” (FG2-P1): “it's a good way to convey the information that you want to get across” (FG1-P2) and “does it matter? Yes, massively” (FG1-P4). However, as the discussions continued, it became apparent that whether it is important (i.e. for researchers) and whether it matters (i.e. to decision-makers) are two different questions. Therefore, providing details about uncertainty is considered important, but when it actually matters depends on the context and who needs to know. When dissecting the difference between the importance and whether uncertainty matters, FG1-P4 concludes that: “uncertainty only really matters when trying to decide what to do”. This is backed up by FG2-P2: “it's important, but the degree to which depends on the context and the policy decision you're informing", going on to conclude that "there isn't a definitive answer really". Therefore, being able to understand and communicate uncertainty is important, but uncertainty only becomes consequential when it has an impact on decision-making.

Communication of quantitative uncertainties to decision-makers was seen as important because "there's no point in giving people a false sense of accuracy, but equally you need to be honest about understanding exactly what the uncertainty is, so you can take action even when you are uncertain" (FG1-P4). The problem that some researchers mentioned was knowing which aspects of the uncertainty a decision-maker is interested in "there's no real rule that works for any end user, it really depends what their need is" (FG2-P2). FG2-P2 goes on to point out "actually your end users don't really care about half of the stuff that you've done, it's then actually working out which of the important bits you communicate across that are really relevant to the decision". Therefore, deciphering what is required for a particular stakeholder creates a challenge for the researchers, so that the user is not overloaded with unnecessary information. This is reflected by FG1-P3 talking about decision-makers: "they don't mind sort of where the bar of uncertainty is, as long as it's smaller, like it could be way off the mark but as long as it's quite a small band then they're happier than a massive uncertainty band, even if one is more accurate than the other". This creates a dilemma for the researchers, they want to present the uncertainty of their research, but if they simplify it too much for a non-expert they could compromise their research.

6.6.2 How is 'uncertainty' interpreted?

The data scientists participating in the focus groups agree that communicating quantitative uncertainty to stakeholders is important. However, when uncertainty is mentioned, the interpretation differs due to the background of the audience. Some understand it to mean inaccuracy and others that something is unknown, for example, FG1-P3 described "from my experience, at least if I've tried to use uncertainty in a sort of less academic setting or things like, that it is essentially interpreted as inaccuracy" (FG1-P3) confirming the previous discussion in chapter 3 and also illustrated by the examples discussed in chapter 5. One reason suggested for this interpretation was that: “uncertainty is not the same as error, so sometimes people use that interchangeably and that's not very helpful because uncertainty is more than error, and they're not necessarily just errors” (FG3-P2). FG1-P1 provides a reason for the interpretation of uncertainty as ignorance: “the difference between, I guess what you might call a binary idea of uncertainty, like do we actually think we know this or not? Which might be more the layperson approach to it". Similarly, FG2-P3 mentioned that “you're not giving a specific number, you've got a variation…you're not giving a number, you're giving a range of uncertainty across that”. As quantitative uncertainty is a point of interest to the statisticians, they find it frustrating that it is interpreted as not knowing and used as an excuse for inaction: “lots of people think that you can’t make a decision until you're sure” (FG1-P4) and “I believe the sort of endless pursuit of reducing uncertainty is not necessarily beneficial, and it can be a sort of deterrent for action” (FG2-P1), so these interpretations create problems when decisions need to be made. The researchers are conscious of these differing interpretations: “it's just being aware of this sort of different interpretations of your explanations and things like that” (FG3-P1) and that they need to “try and communicate in a way that gets your interpretation across rather than someone’s own assumption” (FG1-P3). It is clear from these experiences that consideration of the audience and how the message could be interpreted is very important, so perhaps one way to overcome this is to clarify the meaning at the start of a presentation to any audience outside of the research discipline.

Focus Group 2 discussed the use of models and their concerns that often a non-scientists' interpretation of model outputs was that this was ‘data’ and interpreted as a certain fact: “a model is not something you just press a button and it has a magic answer” (FG2-P2). FG2-P2 went on to mention the advice they were given early in their career: “never mention the word model when you're talking to a customer because they get the impression you're pushing this big red button and get some numbers that are perfect...so we always were told to use the word ‘forecast’ and say probability”. Therefore, the researchers are conscious that they need to provide realistic expectations, make sure that their audience understands that the results provide a variability of uncertainty and that there is not one definitive answer for the problem.

Alongside the problems of interpretation of results, there may also be other considerations, such as resources, that should be communicated. These need to be accounted for if they affect the uncertainties, for example: “what you would ideally do versus what you can do if your client needs an answer next week is very different to if your client needs an answer in five years’ time…if you've not had time or the resources to do uncertainties as thoroughly as you might want, you've got to clearly indicate that so that the decision takes it into account” (FG2-P2). In addition to affecting the level of uncertainty of a decision-maker, this could also affect the level of confidence that a researcher has about their work if they have not had time to explore all the possible uncertainties that could affect their research.

These problems of interpretation create a challenge for environmental data scientists of how to get across their research so that it is understood, as summarised by FG2-P2 “probably the hardest bit is the communicating of the uncertainty”. Presentation and communication of uncertainty emerged as a dilemma for the CEEDS interview group as well as many in the focus groups so it is discussed in more detail in the following chapter.

6.7 Conclusion

This chapter draws on insights gained from three focus groups conducted with members of the cross-disciplinary DSNE project. By delving into the experiences of this group, the chapter has provided a deeper understanding of the types of uncertainty experienced by environmental data scientists, the methods they use to handle uncertainty, and how collaborative environmental data science works in practice. Ultimately, the chapter has shown that although there are significant benefits to scientific research from combining different methods and techniques from different academic disciplines, there are a several areas of tension that need to be addressed.

As explored in chapter 3, statistics provides a means of handling, or quantifying, uncertainty associated with the variability of data. This chapter has contributed to the exploration of the 'statistical theory' dimension of uncertainty in environmental data science. However, although this is often perceived as providing an objective analysis of data, the chapter has highlighted that there are subjective influences which can impact on cognitive uncertainties, creating tensions between different stakeholders. Figure 20 provides a summary of the uncertainties that affect the analysis, communication and interpretation of environmental data science as discussed by the focus group participants.

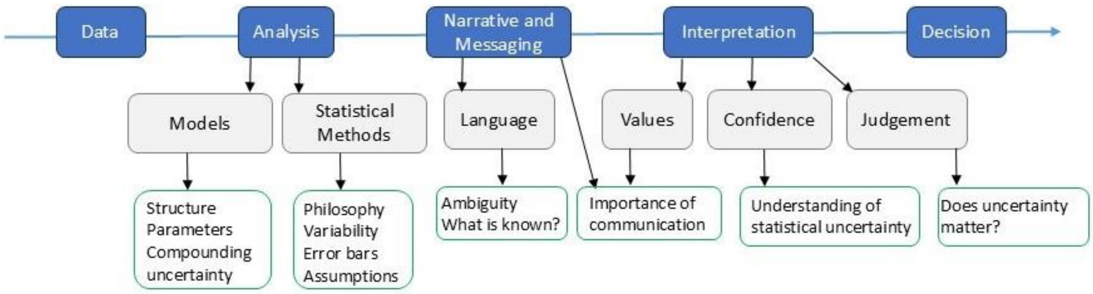

Figure 20. Summary to show areas of tension and uncertainty experienced by the focus group participants

The key findings from this focus group study provide insights into the challenges of environmental data science:

Statistical uncertainty is a specific definition of uncertainty relating to the variability of data, and the distinction between aleatory and epistemic types of uncertainty does not appear to be relevant. However, this definition is not necessarily understood by those stakeholders who don't have a statistics background so it can be a source of misunderstanding and tension. Due to this source of misunderstanding some researchers are reluctant to be fully transparent about uncertainties in their research.

Differing philosophical perspectives between statisticians, and between statisticians and environmental scientists, affects researchers' beliefs and values. Bayesian methods provide a way to incorporate statistics into environmental science, moving researchers away from the objective or realist philosophy inherent in classic (or frequentist) statistics. This enables transparency of subjective uncertainties introduced when making prior assumptions to analyse data. Environmental data scientists with a more application-focused orientation tend to align with the critical/pragmatic realist philosophy, reflecting the realisation that there are uncontrollable aspects to their research.

Communication again emerged as a challenge for the groups – this is both internal within collaborative projects caused by interpretation of disciplinary terminology, and the external communication and understanding of uncertainty to non-academic stakeholders. Much of this reflects the examples discussed in chapters 2 and 3. Improvements to communication, consideration of the different elements and context, would overcome many of the challenges experienced.

The following chapter explores in more detail uncertainties associated with environmental research, particularly relating to data, with a more application-focused group of environmental data scientists.

7 Moving forward under uncertainty

7.1 Introduction

The previous chapter has explored sources of tension and challenges occurring during the production of quantitative uncertainties in environmental data science. This chapter adds depth to this by expanding on other quantitative and qualitative uncertainties, particularly relating to data and analysis. Drawing on interviews conducted with members of the Centre of Excellence in Environmental Data Science (CEEDS), this chapter explores the experiences of environmental data scientists from different environmental sub-disciplines to provide additional insights into the wide range of uncertainties that emerged from the literature review in chapter 3 and building on those developed in chapter 6.

The increasing availability of environmental data and computational developments provide new opportunities for environmental data science, although uncertainties can impact this. For example, if there is insufficient metadata information about the data then its usability is diminished. Other sources of uncertainty discussed in this chapter highlight the problems of quality control of data and analysis methods used for environmental research. These problems can prevent researchers producing the calibre of research that they would like, and although striving to produce trustworthy results, such issues prevent them from being fully transparent about the quality of the data they are using.

The chapter returns to some of the concepts for creating trustworthy science discussed in chapter 2 and considers how they work in practice. Despite the challenges experienced by environmental data scientists, discussed in this and the previous chapter, there are ways that uncertainties experienced in environmental data science can be navigated to enable this new discipline to move forward.

7.2 Summary of method

Semi-structured interviews were conducted with members of CEEDS in order to explore the meaning of uncertainty, its effects and the challenges it creates for environmental data scientists. CEEDS consists of academics from Lancaster University and the UK Centre of Ecology and Hydrology (UKCEH) from different environmental sub-disciplines, as well as computer scientists and statisticians, providing access to thought leaders in this domain (a summary of their areas of expertise is provided in Table 10). The interview group provided access to experts whose experience in a wide variety of aspects of environmental data science matched the requirements for this study; some collect the data they use; others process or model other people's data; and some are involved with data curation. Alongside this some interviewees discussed their experience of working with non-academic stakeholders and policymakers. The interviews in the chapter provide a spectrum of experience along the data-to-decision pathway

Table 10. Summary of interview participants showing their specialist areas

Participant label	**Subject specialism**
P1; P2; P7; P8; P10; P11	Environmental Science
P3; P12; P14	Data Management
P4; P5	Statistics
P6	Computer Science
P9; P13	Environmental Modelling/Application
P15	Environmental Science/Policy Advice

The fifteen CEEDS theme leaders (at that time) were invited by email to take part in the study (see Appendix D). Thirteen agreed to participate, with individual interviews taking place between April and July 2020. Ethics approval for the study was obtained and is available in Appendix A. As discussed in chapter 4 the interviews were conducted with another student. Although some interviewees agreed to be named, it was decided for consistency that the participants would remain anonymous. The interviews were semi-structured to allow further discussion around any points of interest. The questions used as a prompt are included in Appendix E. Due to Covid restrictions the interviews were conducted on-line, they were recorded and divided up to be transcribed by the interviewers. Once transcribed, coding and thematic analysis were carried out by the students individually. Coded text from each interview transcript were amalgamated to look for overall themes, which are discussed in this chapter. Interviewees were asked about their experiences of dealing with uncertainty. The emerging themes that this question prompted related to quality of data, availability of information for reusing data, ways to overcome uncertainty and how uncertainty can be communicated (further details provided in Appendix K). Although there was some discussion with the other student about the interview data early on, this chapter represents reflections on the themes by the author, alongside reflections of how these interviews relate to the literature discussed in chapters 2 and 3.

Following the CEEDS interviews, the author conducted two further interviews which provided additional in-depth insights into areas of limited discussion with the original interviewees. These were with a CEEDS member, mentioned by P3, who has experience with data collection and publishing data-related papers, to gain a more in-depth understanding of their day-to-day work. Additionally, the opportunity arose to conduct an interview with someone who had worked in a research role (not a member of CEEDS) and moved into an environmental policy advisor role, providing a cross researcher/decision-makers perspective. Both their thoughts are included in this chapter and included in the table as P14 and P15 respectively.

7.3 Sources of uncertainty in environmental data

This section looks at various sources of uncertainty in environmental research. Interviewees were questioned about data collection, so this section includes their responses, alongside the emerging theme of how the interview participants control the quality of the primary and secondary data they use. Quality control of research is one of the tenets for helping to reduce some of the uncertainties seen in post-normal science (Funtowicz and Ravetz, 1990; 1993). It provides a means to understand the calibre of the research results, particularly when they are used by decision-makers. With the large volume and variety of environmental data being collected, the veracity of this data is important. Quality control provides a means for a researcher to decide which data to use and informs their level of uncertainty about this data and the subsequent results.

7.3.1 Collection of primary data

Environmental science datasets are collected in a wide variety of ways, described in chapter 2. These can be either via instruments or by human collectors. Environmental data collected by instruments are perceived to provide unbiased data, for example, P4 stated: "mechanically recorded...aside from a mechanical failure, that sensor is trustworthy…it's designed to do a job and is just recording it without human bias". However, this quote does not consider the human influence of instrument positioning which could affect the outcome of the research. P4 did go on to mention this, using the example of locating air quality sensors close to sources of pollution, e.g., next to roads, adding that this type of bias is not a problem if it is acknowledged. Ultimately, this shows that it is difficult to remove the human impact from data collection. Additionally, it should be noted that instruments have their limitations and can have inherent biases, for example, particulate sensors can be affected by high humidity.

The rest of this subsection focuses on two examples of data collection methods discussed by interviewees P2, P5 and P14. These methods are unique to environmental research and rely on expert observations for collection, rather than the use of any instrumentation. The examples are the vegetation studies as part of long-term monitoring surveys to detect temporal and spatial environmental changes, and the collection of observations by the public.

The use of long-term monitoring surveys was discussed by P5 and P14, who are involved with the design and coordination of land-use and vegetation surveys, along with the analysis of the resulting data. One example that they mentioned is the Countryside Survey of Great Britain, which has monitored land use and biodiversity changes since 1978 and is the longest running monitoring survey of rural landscape in the World (Countryside Survey, 2007). Over this period, in addition to the detailed vegetation plots the survey has collected, and continues to collect, a large amount of data on freshwater ponds and streams, landscape features, and aspects of soils.[20] Various problems have been experienced which affect the consistency of the vegetation data over time, such as changes in personnel and land access permissions to monitoring sites (P5; P14). However, technological advances, e.g., replacing handwritten records with a digital form used for collecting vegetation data in the field, have improved recording accuracy (P14). Regarding collection of observation data, P5 admits “a lot of the data that we collect from the surveys can be messy, or although you design something, and you expected the design to be nice and straightforward things happen, you can't control everything out there in the environment”, highlighting that there are unavoidable uncertainties in the data. All field surveyors are trained to use the same methods and managers regularly check for missed or duplicated plots (P14); however, this is not foolproof. P14 described how the vegetation plots are quality assured (QA) by an independent assessor, with about 10% of the plots re-surveyed and used to produce a QA report. Any recording errors, such as misclassification or incorrect coverage of vegetation, are quantified and adjustments applied to the full dataset where necessary (cf. Countryside Survey, 2007). A formal quality assessment process and availability of a QA report, such as described, provides a way to make sure that there is accountability in a dataset. It provides a means of indicating that it is a trustworthy resource for anyone who wishes to use the data, and can reduce their level of uncertainty in the dataset.

The second example, collection of biodiversity data by the public or ‘citizen science’ was discussed by interviewees P2 and P5. This method of data collection was introduced in chapter 2. It makes use of public observations which are usually submitted digitally over different timescales, for example, at a specific time (e.g. the RSPB’s annual birdwatch[21]) or can be submitted anytime to track the spread of invasive species (e.g. harlequin ladybirds[22]). Interviewee P2, who has experience of collecting and analysing this type of data, discussed that there are concerns within the research community about citizen

[20] for more details see CS Survey data | UK Centre for Ecology & Hydrology.

[21] See Every survey counts. Tell us what you saw by 23 February.

[22] Citizen scientists map the rapid spread of harlequin ladybirds | UK Centre for Ecology & Hydrology

generated data, stating: “there is a general distrust in academia in citizen science data because it is not collected using protocols, so it contains biases”. Confirming this and providing an explanation of their personal distrust, P5 stated: “I am always...not sceptical, but you’ve always got to be careful with citizen science data because you don’t understand the motives of how the data was collected and the decisions that were made... you’ve had no control over how, why, or when people collected data, and not only do you not have control over it, you don’t have any information on that either". Clarifying a context to this, P5 went on to say that their concerns relate to the use of this data for studies of plant or animal populations as data is more frequently captured in easily accessible locations. Therefore, P5’s level of uncertainty for this type of data is high. However, P2 described how they are involved with the development of apps to be used to improve accuracy and provide a means of quality control of public submissions (e.g. https://irecord.org.uk/ for wildlife observations), which enable observations to be easily verified by experts who “look at the records that are being made, look at where they are on the map, look at any photos that came in accompanying those observations, they can quality check there too and records in iRecord are only used in analyses once they've been through that expert verification process” (P2). Although this method addresses accuracy of data submission and potentially reducing uncertainty levels in users, it does not address the other concerns raised by P5 such as unbiased population coverage due to the location of sightings.

This subsection has highlighted some types of environmental data collection, where problems can occur leading to uncertainty, and methods used for controlling the quality of the data. This is important for those who use data collected by others to ascertain any shortcomings of the data that could affect their level of uncertainty and their confidence in their results. The following subsection discusses some other problems experienced by environmental data scientists when using environmental data collected by others.

7.3.2 The use of secondary data

The drive for open science has encouraged the emergence of the data repositories discussed in chapter 2, making access to secondary data much easier for the environmental data scientist. Access to these repositories or databases can range from open access, i.e. open to anyone, expert or amateur, to add or make use of data, open with elements of QA of the data, or managed, whereby there are checks on the data and metadata before datasets are made accessible. This section discusses the experiences of the interviewees of using or managing specific data repositories. One interviewee (P1) discussed how they had reduced their use of open access databases because there is no control over who submits data, creating concern about errors and biases in the data and hence data quality: “there's issues in that around who's recorded it because some of it is so subjective, especially with things like which species is it?” (P1). P1 added: “nowadays I more use my own data” although they also mentioned that they were happy to use data collected by trusted colleagues working on collaborative or similar projects. However, sometimes it is not possible to collect data due to time or location, so P1 concludes that: “people that use it [open source data] tend to do what they can with sort of checking if it makes sense” along with: “thinking about whether that kind of data is okay for the question you're asking…is it okay if there are a few small errors in the data? And if it is okay, then it's probably alright to use but if it's not okay then don't use those datasets” (P1). P1 went on to say: “I guess just being really transparent about the quality of the data is the most important thing and I think generally that is what happens with those databases, that and people don't try and pretend it's perfect but it's like, well, this is the best we've got”. This transparency relies upon the honesty of the data user to declare their knowledge about the data quality. By collecting their own data and using data collected by colleagues they trust, P1 can control their data quality and reduce their level of uncertainty in their research.

The alternative to open repositories is managed data centres, where datasets are only added after certain standards are met. These are overseen by data managers who make sure that the data deposited is of sufficient quality to be useable by other researchers, including having sufficient information about data collection methods (P3). However, P3 highlighted the opposite side to this, which is the difficulty of persuading people to submit their data, often due to concerns about receiving recognition: “’why would I as a data creator, give it to you? Why don't I keep it to myself? — publish my own papers...which might be...easier and I'm going to be first author from that’. So there's a real big issue around their trust...to give them some sort of reward or recognition for providing data" (P3). Along with P3, P5 also discussed the problems of how to motivate people to submit their data into data centres and provide information about the data: "there's a bit of a cultural thing, which is that some people see putting their data in the data centre as something they have to do or something they've been told to do, and it's an annoyance and frustration, and they don't want to do it" (P5). Reflecting P5's quote, P6 concludes: "I think there's still a lot of challenges when it comes to dealing with data in general and there's still different attitudes towards opening data". P3 also expressed a similar response, proposing that to get researchers to submit data needs "a different mindset... an open science mindset" to see the value in sharing their data. P3 added: "I think we're still back in the 20th century idea of, you produce this paper, and it has a dataset which has some dry, technical page and that's how people gain trust in things, that's not how people do it at all", reflecting the 'normal science' mindset. One option that P3 suggested to overcome this is promoting the value of publishing papers about data into data journals (e.g. Wood *et al.*, 2017; 2021), stating: "loads of people go to...ferret around and see if there are useful datasets", confirming that there is an audience for this type of paper. Other incentives to deposit data into managed data repositories for others to use could be a guaranteed acknowledgment, or even inclusion as an author on peer reviewed publications (P3). These options provide a means of gaining recognition for providing data that is available to others and increases the visibility of their research. P3 went on to say that these problems have still to be resolved: "we're still thrashing about at the moment", but database managers argue that they are providing a trustworthy resource to support the data collector with open science (P3), which is often a requirement for publicly funded research.

A significant problem with using secondary data is the provision of information about a dataset, known as metadata. The importance of having this information was discussed by over half of the interviewees – "I think in an ideal scenario, as a scientist, you do want quite detailed metadata...in terms of tracing the data, it can boil down to things like were the trees' measured above the buttress roots" (P10). The metadata provides an indication of the quality of the data and affects the results that can be obtained. It creates a source of frustration, or 'data friction' (Edwards *et al.*, 2011), as described by

P9 “it's a nightmare, people...don't understand why it's important” and P4 “someone gives you data and...hasn't really thought about what you, who is analysing it, what you're actually going to do with it”. However, a pragmatic reason suggested for why metadata is missing is due to lack of time (P9, P13), epitomised by this quote: “it's the concept versus the practicality of busy people, lazy people, stressed people” (P13). As this quote indicates, the provision of metadata is time consuming and this effort is not always rewarded, as P2 notes: “my manager is ‘oh right, well we will write the right documentation’...And I’m like, ‘yeah, yeah, yeah, no one will read it!’”. However, as P10 states “even if you don't intend to read the metadata cover to cover, knowing that it's available should you want to, might kind of give a bit of a different feeling about the data”, indicating that it provides a proxy for data quality. Unfortunately, some data providers do not see a value in producing these additional details; they take time to produce and may not be used. These opposing views, as discussed in the previous paragraph, affects the availability of good quality data and overcoming these differing values of data is still to be resolved (P6).

It is clear from the above that there are significant challenges when collecting or locating empirical data for producing scientific evidence for decision-making. The quality of this underlying data is important as it feeds into analyses and produces the results needed for evidence, therefore if data is unavailable, or a researcher is not confident with the quality of data they have used, this will then affect their level of uncertainty or confidence in analytical outputs. Assessment of data quality is fundamental for realising what and where uncertainties are occurring and deciding on how these should be dealt with.

Once the environmental scientists have obtained suitable data, the next step on the data-to-decision pathway is analysis, which exposes more uncertainties for the environmental data scientist to contend with.

7.4 Sources of uncertainty in environmental data analyses

Knowledge about data quality is important for maintaining the quality of the subsequent data analysis. As discussed in chapter 3, the UK government provide “guidance for producing quality analysis for government”, the strapline for The Aqua Book (Treasury, 2015). Several interviewees mentioned that they follow these guidelines for their research, however, they did not elaborate on the specific guidelines they use. For example, P9, when referring to a new project, stated: “we've kind of agreed the details of how we will ensure that we're compliant with the Aqua Book approach” and P11, when discussing the assumptions made: “we've created a sort of QA document of that process…it is us sense checking the results and…us having a documented trail linking to Aqua Book standards that shows we’ve got that”. These quotes are from environmental modellers, but it was clear from all the interviews that quality of environmental data and its subsequent analysis were at the forefront of researchers’ minds. However, specific quality standards, as discussed in chapter 3, were not mentioned by any participants.

7.4.1 Metadata and assumptions

Insufficient metadata (discussed in the previous section) affects the ability of the data user to determine the quality of the data and to make use of it. However, if datasets are limited for a specific research area then it may be necessary for the environmental data scientist to use what is available, even if metadata is limited. As P4 states: “the reality is that we never have enough information”, explaining: “it's often the case, it's just because someone gives you data and whoever's collected the data hasn't really thought about what you, who is analysing it, what you're actually going to do with it”. Therefore, it is necessary for the data analyser to make assumptions: “we make some assumptions...this is the key thing, actually, behind all of statistics...there's always an underlying assumption you have to make, if you don't make assumptions, then your uncertainty is just infinity, right? Because you don't know everything...the more assumptions you impose will reduce the uncertainty that you have” (P4). As this quote shows, assumptions are vital to carry out environmental research and provide a means to reduce a researcher's level of uncertainty: “assumptions that you make will define how certain or uncertain you are about something” (P4). However, as P5 points out: “there's a lot of uncertainty you are ignoring in the assumptions that we're making to get to that point, there's a lot of uncertainty in those assumptions” going on to say: “a lot of times these assumptions are hidden or not really well understood by practitioners, and I think that's something we need to convey more” (P5). Moreover, assumptions introduce a subjective element to the analysis as they are usually based on experience and judgement, as discussed in the previous chapter (section 6.5.1). However, as highlighted by the ozone story in chapter 5 assumptions may not be correct, with the assumption that the instrument data was erroneous delaying publication of early research. Similarly, as discussed in chapter 2, the presence of alien species (e.g. in a data repository) could be assumed to be an error in the data but may be an indication of an invasive species. Therefore, assumptions about anomalous data need to be considered carefully as outliers may be meaningful and represent a new and genuine environmental concern. The lack of details provided for the decisions that are made to produce the assumptions was discussed by P5: “what assumptions...have been made, which isn't always recorded. And if there are subjective decisions, then how did that come to or, what might other plausible decisions have been”. This paragraph highlights once again the lack of, and need for, more documentation about assumptions and decisions that have been made to produce the research results. As discussed in the previous chapter, recording the assumptions and decisions provides additional transparency about the research. For a decision-maker, access to these details provides a means for them to assess their own level of uncertainty, depending on whether they agree or not with the assumptions made.

7.4.2 Combining datasets

An emerging feature of environmental data science, mentioned in the interviews, is the combination of datasets from different sources, described by P5 as “an interesting aspect of research at the moment” and P10 “it's definitely an active field of research of how we can kind of fuse this different information, different data”. Often called ‘data fusion’ (Castanedo, 2013; Gibert *et al.*, 2018) this was discussed earlier in chapter 2. This emerging application is due to improving technology, as noted by P10: “as computing capacity has...increased we're able to do things that are much more complex than before...this idea of bringing together datasets from different sources”. However, methods to combine datasets are not without problems, as P5 mentions: “how you do that appropriately and in a consistent way is actually quite challenging”. Combining datasets creates a new avenue for uncertainties, for example “using ground-based data alongside remotely sensed data, so it's kind of marrying those two up and yet you often get sort of discrepancies between the two and scatter around those relationships” (P10). Other problems described by interviewees relating to this are, differing units: “one that I always come up against is units...where data may have been converted and stuff like that, there's a level of uncertainty around whether or not that's been done correctly” (P15) and making sure that the data included is as up to date as possible: “using data that's out of date or old or needs updating...I wouldn't say it's been a problem, it's just something that we have to assess in our confidence” (P15). These latter two problems are not exclusive to combining data but need to be considered when using such methods. They are also considerations that are important for decision-making and affect levels of uncertainty or confidence in results as mentioned in the quote by P15.

7.4.3 Appropriate use of methods

The appropriate use of statistical and analytical tools was another important issue mentioned by several interviewees, summarised by P10: “I think that's another sort of important point about making sure that people are using the right tools for the right purposes” highlighting that “people from the outside might not necessarily know what an appropriate tool looks like”. This comment was prompted by what P1 - and P10 - considered the inappropriate application of a species distribution model to Covid data. They were both frustrated by a paper published on this by a highly cited academic in their field, with P1 stating “they must have known that this was a terrible thing to do” and commenting: “he doesn't have much integrity, let's put it that way, and just sort of wanting to get a big impact quick paper”. Additionally, the results were picked up by the media, so P1 was concerned that public were misled by this research: “we can see right through it really fast, but the general public can't because why should they be able to see that, and this guy, he's published it, he's won loads of awards and things like that, because he's had all of these big papers, and so if you looked at his profile, any normal person would probably say, ‘Oh, yeah, he looks really trustworthy, he's a really eminent scientist’” (P1). This highlights a difficulty when judging who to trust, and that sometimes cues used for this, such as reputation, cannot always be relied on. An additional consequence of this is that the science user will feel more certain about the scientific evidence being presented than they should be, potentially leading to an incorrect decision.

Another controversy mentioned by P5 is the use of statistical techniques in some disciplines (e.g. psychology) to manipulate data: “actually in the sort of quest for making this objective, a lot of the rules of statistics have sort of been ‘abused slightly’ shall we say?...you may have heard a lot about these arguments relating to statistical significance and P values” (P5), but it is not necessarily a problem with the technique used, as P12 stated: “if someone's using a method in an inappropriate way it could make the method look bad when the method should never have been used for that application anyway”. Both of these examples illustrate that when methods are used incorrectly this is not obvious to a non-expert, so P10 suggests that there should be “collective responsibility to make sure things are used appropriately”, and in doing so calling out misuse of methods so that the whole research area remains trustworthy.

This subsection also relates to credibility as discussed in chapter 5. If trust in methods or research areas are questioned, then this can affect the credibility of others who use these methods or are researching within the same discipline.

7.4.4 Quality and trust

Returning to the use of open or managed databases for obtaining secondary data, discussed in the previous section, the difference between the two databases is trust in the intentions and expertise of the data collectors, and relates to the discussion in section 2.4.4. In open databases the expertise, or ability, and or integrity, of the data submitter is not transparent and therefore the data user can feel that this is less trustworthy (e.g. as discussed in section 7.3.2 by P1); whereas quality control provided by the “[managed] data centres like data.gov.uk, that’s why they are sort of good, because it’s a trusted site, that in itself gives you some sort of sense of well ‘this is trustworthy data’ y’know?” (P5) and provides an indication of benevolence. Therefore, the commitment and expertise provide a means of trust, as noted by O’Neill (2018), which is important for the scientist to make a judgement about the quality of the data or analysis. Moreover, having trust in the data, or the person who has collected or processed the data used, can help reduce the level of uncertainty of the researcher. For example, P13 stated: “if the maths is too complicated for my brain to get round, I struggle to trust it, that said, if somebody brighter tells me that it makes sense it, and it's all fine, I can be persuaded”. However, P15 described a situation when they found an error with some data they had used in a report, causing “a loss of trust where we thought, ‘oh, OK, well, we need to check everything else now’”, thereby highlighting that trust was lost after this one mistake and P15’s level of uncertainty had increased about all the work that this third party had carried out.

These sections on collection and analysis of data have confirmed that environmental research is rarely carried out by individual scientists in isolation. Much of the research relies on collaboration and can involve working with unfamiliar people from different disciplines, which creates a source of tension, as discussed in the previous chapter. Uncertainties arising from working within cross-disciplinary teams emerged from the interviews, which contribute insights to both the communication and cognitive aspects of uncertainty, and the messaging, narrative and interpretation steps on the data-to-decision pathway.

7.5 Uncertainties of teamwork

7.5.1 'Science friction’

Environmental research which produces results to be used as evidence for decision-making often requires collaborations that cross disciplinary boundaries, creating challenges for the researchers. Illustrated by P13, who stated: “people are in their disciplinary mindsets, they don't think interdisciplinary by default”, creating what Edwards *et al.* (2011) describe as ‘science friction’. P13 described their experience of an interdisciplinarity meeting where people discussed the importance of this type of research and “was surprised at the number of people who responded with, ‘because funders want it’ rather than actually understanding that there are the legitimate advantages in it”. P13 went on to say that “they see it [interdisciplinarity] as a distraction from what they're trying to do or what they're trying to understand”. The differing viewpoints of academics regarding cross-disciplinary research was also described by P8: “the degree to which people are prepared to engage in multidisciplinary research and the degree to which people value multidisciplinary research is quite variable”.[23] These different values, or mindsets, reflect the differences between those who prefer to remain carrying out ‘normal’ science and those who are prepared to undertake post-normal science. These differing perspectives can create a barrier for cross-disciplinary collaborations and be a source of tension, or friction.

Alongside values and mindsets, some other reasons discussed by the interviewees that contribute to tensions or frictions within collaborations are language differences and disciplinary research expectations. Interviewees P6, P8, and P10 discussed problems with language and communication while working as part of cross-disciplinary research groups. As discussed earlier in chapters 3 and 6, each discipline uses its own jargon and has different understanding of wording, for example P10 stated: “I think there will be challenges because…you've almost got people kind of talking different languages” and P6: “differences in vocabulary was a little bit tricky to get over at first...the first number of months it was, a matter of ‘what do you mean when you say this word? What do you mean when you say that word?’”. It can therefore be frustrating when members of a group do not understand, or have a different understanding, of what others are saying, leading to confusion and misinterpretation.

The timing of involvement of different disciplinary researchers in the research process can create problems and affect the research outcomes. P4 was frustrated that “there's always this issue that statisticians and people who analyse the data, the data scientists,

[23] Interdisciplinary and multidisciplinary were used synonymously by these interviewees.

are always at the very end of the process are not there at the beginning of the process". This is in reference to data collection, whereby the statisticians are not involved in the project design and then are expected to produce results from the data they have been given. Also mentioned by P5: "you've had no control over how, why, or when people collected data", which then affects the quality of the results that can be generated, and requires assumptions to be made, as discussed earlier.

Different research expectations and disciplinary cultures were another source of friction when working within cross-disciplinary groups, discussed by the interviewees. P8 described different disciplinary publishing expectations, for example, the expectation within environmental science is one paper per year, whereas a higher frequency is expected within computing and statistics. P6 discussed practicalities of sharing data, including an example of a project where bureaucratic "red tape" prevented members gaining access to each other's data within the same project. These can create a source of frustration — "how does it work in practice? In practice it probably has people being very human about it, getting very cross with people that they should probably just try harder to understand" (P13) and a need to "understand some of the kind of idiosyncrasies of how people talk about things which partly reflects them being from a different kind of research background" (P9). P6 summaries this challenge stating that the "challenges are not technical models, but are cultural, and I don't think we have a solution to this yet". It is clear from this discussion that there are various sources of friction created when researchers from different disciplines work together. The acknowledgment of these differences and development of ways to overcome them, along with having a shared goal to solve complex environmental problems, encourages tolerance and enhances collaboration.

Although working with different disciplines presents several challenges some people are prepared to overcome these and are positive about, and excited by, this type of collaboration, for example P8 stated: "I strongly welcome a move towards multidisciplinarity, I think we can do a lot more interesting things a lot better that way". P7 was also positive and mentioned the excitement they feel: "I've kind of moved to now…to try to think about those things more broadly and trying to embrace more disciplines, which I've found much more exciting”. However, forming collaborative teams and finding people to work with from different disciplines presents another challenge discussed by interviewees P6 and P8. Reputation, in the form of expertise, was suggested by several interviewees as a way to find trustworthy collaborators, this could be by paper citation (P2) or by recommendation from someone else they know and trust (P1, P8), e.g. “I guess reputation is a big one, so scientific reputation, someone who's well respected in their respective fields, you don't necessarily have to know the details of what they do. But you have to know they're good at what they do” (P8). Trust provided by expertise takes out some of the uncertainty of working with others, for example, P8 stated: "I don't have the statistical or computational abilities and skills that are needed to do some of this work, so I have to do it in collaboration with experts like [x], or [y], so there's definitely an element of trust there". This shows the importance of expertise for being seen as trustworthy, along with the expectation of commitment (O’Neill, 2018) or integrity (Mayer *et al.*, 1995). The preservation of reputation ties in with the discussion on credibility in chapter 5, so part of the trust input to a collaboration is the expectation that it will not damage your reputation (P2).

This exploration has exposed many challenges the scientists face when working with people from different disciplinary backgrounds, with some questioning the value of undertaking this type of research. However, there are others who view it positively and ways of overcoming the problems and frictions are being developed.

7.5.2 Ways to move forward

Although working in cross-disciplinary teams presents challenges, the benefits of working in this way can make it worthwhile, as noted by P13: “quite often you find somebody who's just done some interdisciplinary work, and they’re like, 'Oh my goodness! Have you tried this? It's amazing!' and that’s because you're getting different insights on different angles and people”. P13 goes on to suggest what is needed to go forward: “a lot of it is about finding a way through, that you've been as clear as possible and building that shared understanding so that you're teaching them and you're learning from them”. P6, P10, P11, and P13 discussed various methods ‘to get to a common ground’ and aid collaborations, however, as discussed working within a cross-disciplinary group requires a researcher with a different mindset to realise the potential benefits of this. For those prepared to follow this path, the following methods to overcome some of the challenges were suggested by interviewees. These methods would be beneficial individually, but if used in conjunction with each other would help to reduce some of the tensions described earlier.

- **Collaborative research environments**

Collaborative research environments, also known as virtual data science laboratories, were introduced in section 2.5.2. This emerging research tool provides a virtual research environment that allows collaborators to access, manipulate and analyse the same data and share expertise. P12, an advocate of this method, stated: “the environmental scientist can understand the assumptions of the statistical model, what's happened, what's been done to get to the answer...I see that as a way of getting a bit of trust in the resource because you can see fully from start to finish what assumptions have been made and what people have done”. These virtual research environments enable transparency, providing a “provenance of what's happened” (P12). Moreover, they can provide an aid for cross-disciplinary collaboration. When discussing problems of working with different disciplines, P6 stated: “I'm hopeful that things are getting better if we build these collaborative research environments”, providing optimism that use of this type of virtual research environment will develop and provide a medium to improve transparency in collaborations.

- **Co-production**

Three interviewees discussed their experience of transdisciplinary research, which has involved all stakeholders in co-production or co-design of the research. The problems described previously – language, understanding, values of the different academic and non-academic partners – will affect this type of research. However, the advantage is that the stakeholders have input into the project design, input into assumptions made, they see the research process, what is and isn’t possible and can question any values or biases, with P13 stating: “I've actually been really impressed with the kind of iterative back and forth with them”. It provides means of awareness of what is required:

“whenever we met with the local communities...always extremely eye opening and very insightful in terms of what are the things they actually care about” (P6); and transparency of decisions made: “stakeholders can feed into the design of things so that...you can kind of build something that everybody wants” (P10). Co-production with stakeholders can enhance the research process, helping to overcome some of the uncertainties of the decision-makers, and can make sure that the research moves forward in the desired direction and in a timely way.

- **‘Bridging’ People**

Several interviewees suggested that there is a need for people who can connect between all the stakeholders to overcome the problem of language and cultural uncertainties. For example, P8 noted: “we need a lot more people in the middle so a lot more what we call bridging scientists, so people who are trained in technical skills but also have a knowledge of the…environmental sciences as well” and also noted by P10: “I think what's important then is as a community to sort of build up the expertise and having people that kind of bridge these different things which will enable us to tackle these really big questions that involve looking at different components of systems”. These people would need to have an interdisciplinary background and be able to facilitate between the different groups, as P13 notes: “the advantage of somebody who is trained in the middle deliberately is that they are naturally able to swap mindset relatively easily and have the understanding that one mindset isn't right or wrong”. These facilitators would have an overview of the whole project and ability to pick out any possible areas of conflict, however, they need to be included as part of the initial project budget (a consideration often overlooked).

- **Time**

As mentioned in chapter 2, funding bodies are increasingly requesting cross-disciplinary research. However, the grants they offer do not allow any extra time to overcome any initial disciplinary differences. Additional time would be beneficial as “it takes a little bit of time to establish multidisciplinary relationships…establishing a way of communicating, so the way in which statisticians work and communicate and priorities that drive their research are completely different from an environmental scientist -

learning how to communicate with each other has been really important" (P8) and "if you give people enough time to get to a common language and a common understanding, actually, you can start to see what can and can't be done" (P13). This shows that there are relatively simple measures that could be incorporated to improve cross-disciplinary collaborations and outputs given extra time.

It is important that these resource issues – people, time – be addressed as they could make a big difference to the outcomes of cross-disciplinary research projects. Therefore, even though these would require additional funding, the benefits could outweigh this.

7.6 Communication of environmental research

The previous sections have explored sources of uncertainty relating to environmental data science – data, data analysis and research collaborations – which the interview participants have experienced. This section continues the communication discussion from section 6.5 in the previous chapter but looks more specifically at the challenges of presentation of results and transparency in environmental research, which emerged from the interviews. Again, the chapter draws on the experience of the interviewees to investigate how they communicate their results to decision-makers and provides a vital link between data and decisions. The section provides important insights for the messaging, narrative and interpretation aspects of the data-to-decision pathway.

7.6.1 Presentation of results

Several of the interview participants discussed the communication of uncertainty to decision-makers. As discovered in the previous chapter, communication of research presents a challenge to the environmental data scientists, confirmed again by some of the CEEDS interviewees, for example, P5 noted: "communicating uncertainty is really difficult and challenging and what policymakers in particular sort of think of as uncertainties is very different to what I might think or someone else might think". P9 highlighted the importance of communicating the meaning of uncertainties to decision-makers: "for me it's really important to keep in mind the kind of potential impacts of somebody making the wrong decision based on poor quality information or information that hasn't been communicated properly”. This quote reinforces the importance of considering the message and narrative aspects when translating data for decisions.

The interviewees in this study had a range of experiences of engaging with policy decision-makers, some had no experience and others much more. Several interviewees mentioned their difficulties of knowing what to present to policymakers, stating that in their experience, the policymakers “don’t like uncertainty” (P3), prefer that “numbers are a bit more black and white” (P10), and “they still just want that headline figure of ‘is this good or is this bad?” (P5). This desire of decision-makers to be presented with a simplified version of results makes it difficult for researchers to present complex problems, for example: “the desire is for just like one number to represent things...there were some instances where they didn't understand something and it was a bit painful to try and explain it“ (P9) and “I think this is where the whole communicating uncertainties are quite an interesting arena because you're not just looking at a kind of a one number it's, it's more complicated than that, so you have to get a bit more creative about sort of doing that” (P10). P2 also discussed their concerns about how well results are understood: “I do sort of worry about the imbalance between the amount of effort that people like us put into creating these error bars and making sure that errors are propagated through and are there on the graph and the ability of our audience to understand the meaning and nuance”. All these quotes describe the difficulties of communication, epitomised by the following quote from P5: “it’s that trade-off between having something that is understandable and interpretable...to whoever the audience is, versus something that conveys the detail, and the uncertainty”. It is clear there is an incompatibility between being open and transparent about all possible uncertainties, as against making sure that the information presented is relevant to the audience, since too much information could be equally detrimental if it is not understood.

Stakeholders involved with an environmental problem can range from the public to the decision-maker, all of whom will have different backgrounds, levels of understanding, and different aspects of the research that they are interested in. With regard to decision-makers, P13 observed: “policymakers are not one thing...they have different abilities to respond at different levels, they have different constraints and different things driving them". These different audiences will have different interests in and reactions to the research, as noted by P8 "numbers that seem either trivial or alarming, depending on your perspective. And I think it'd be really interesting to do some work around just untangling that a little bit, so 'What is the number? What is uncertainty? Is it trivial? Is it alarming?' How do you communicate it in such a way to get the relevant impact level across to those groups?". Similarly, P5 suggests: "I think that's what's needed because what does- there's not that extra step of translating a significant result into "Well, what does that mean? Is that meaningful?". As these two quotes show it is the impact of research and the uncertainty that these interviewees feel should accompany the research results, and which would aid a decision-maker to understand what is going on. This confirms the relevance of using risk as a means of communication, as discussed in chapter 5. P6 mentioned a project they were involved with where they provided information on potential impacts: "also give them [stakeholders] guidance about how to interpret this data because obviously not all the users are familiar with interpreting such a graphical format...What does this mean for my land? Does this mean my house will be flooded? Or does that mean just the far end of my land will have a little bit of a puddle in it". One method used to present results to policymakers is the use of a traffic light system, mentioned by P5 and P15. This method of allocating red, amber, and green for potential impacts allows a decision-maker to ascertain the severity of an issue, which relates to the risks of the impact of an environmental problem.

Alongside concerns around how to present results so that they are understood, some interviewees were also concerned about how results could be interpreted and then represented by others. P9 worried that once results were disseminated then the researchers "lose control", so "you also have to be careful about the headlines that get picked out" (P11); a similar description to the problem described by Pyle in chapter 5. Unfortunately, this is a difficult problem to solve, except for making sure that there are no ambiguities in the results which could be misinterpreted. P15 discussed a circumstance whereby the locational context for a piece of research was purposefully missing from the communication, so although the scientific result was correct it was ambiguously communicated to affect the message being put across. In this case, it suited the messenger not to be fully explicit, so the presentation of the information was distorted and not transparent.

7.6.2 Transparency

The previous sections have shown that the interviewees were cognisant of being trustworthy, and transparency of uncertainty provides a way for others to judge this. Reflecting on the interviewees responses suggests that transparency could be divided into two different types — relating to either quantitative or qualitative uncertainties. Advocating quantitative transparency, P11 states: “I think you have got to be open and honest about the uncertainties” with P12 suggesting that “I think it makes people trust, oddly, if you quote uncertainty on your data, I think it makes people trust your data more, because they don't think you're trying to hide anything” (P12). However, transparency to other participants includes a more qualitative approach: “documenting and having a clear narrative on why you took the approach you did or why you took the data you did is a trust building exercise” (P3). By supplying details of the assumptions and decisions made to create the results, along with uncertainty estimates, provides a means of visibility of the knowledge creation process and quality of the results. This in turn provides awareness of the process to others, and hence a means of determining the accountability of the knowledge creator. Erickson and Kellogg (2000) recognise these three features – visibility, awareness, and accountability – as the properties for their concept of socially translucent systems. Translucence recognises that the social system is not totally transparent and some areas will remain opaque to others (Erickson and Kellogg, 2000). As discussed, interviewees have experienced problems with metadata, lack of documentation, etc, all of which create obstacles for full transparency. It can also be argued that the desire to remain impartial, discussed in chapter 5, contributes to this translucency. Ultimately, transparency (translucency) and accountability enable the information receiver to decide the level of trust they place in the results. One method, which attempts to incorporate all three features, was suggested by P13: “my answer to most environmental stuff is you want as much information on the table, so the best available knowledge, and you want the right people around the table to discuss that knowledge to try and get to an actual understanding”.

In this situation all information is visible, along with awareness of the sources of knowledge, and the in-person aspect enhances accountability (Erickson and Kellogg, 2000). This provides evidence for others to judge whether they trust the other individuals and the knowledge they are presenting, thereby affecting their level of uncertainty about the evidence presented.

Another potential cause of translucency, created by the demand for open research, was highlighted by P5 who described how the requirements for additional information had changed over time and was concerned that "if everything's open all the time, it means you never get to move on". This obviously raises concerns for reproducibility and questions the practicalities of open science as time passes. Alongside this, people change jobs or careers so knowledge about the data or research is lost or forgotten (P5, P7) and technology moves on, e.g. "the machines that you ran it on don't exist anymore, so it's unlikely that you're going to get exactly the same result" (P3). P4 summarises these problems and the difficulty in overcoming them, stating: "that's the real challenge - how do you make reproducible and trustworthy research? I think it's still something that I don't think has been fully understood yet". These examples draw out compelling points that highlight the difficulties for the scientists of maintaining open and transparent research over time.

Although being transparent was important for many interviewees, P1 and P5 described situations where they felt they could not be totally honest about the quality of the data they had used to get their results. P1 stated: "you obviously can't be too disparaging about the data you're using...there's always like this fine line that you have to walk of trying to be as transparent as you can and saying what the limitations are without undermining what you have done"; and P5: "the scientists are so driven by publications and publications are sort of themselves driven by sort of having 'good data' in quotation marks, that show something interesting you don't want to say that your data is terrible…but you don't want to expose any potential weaknesses in your data because that might undermine your results, and you want results that are clear and seemingly objective**"**. Therefore, although the scientists aspire to be transparent and trustworthy, there are times when this is overridden by other values. In the following example the value is getting papers published, P4 stated: “it doesn't pay to be honest, perhaps, so there are lots of stories in the last couple of years about people who've been dishonest with their research just because they thought it would get their paper published”. Getting journal papers published provides reputation, credibility, and career progression. However, while academic careers are judged on journal papers it could be questioned whether full transparency is achievable or whether some aspects of research will continue to be hidden, or undisclosed. As discussed previously, this feature of ‘normal science’ also creates problems for post-normal challenges.

7.6.3 Principles of environmental data scientists

An overarching feature of environmental data science is cross-disciplinary collaboration to move along the data-to-decision pathway. Placing trust in others is therefore a vital part of this, and emerging from the previous section is the desire of most researchers to be seen as trustworthy. The principles that they have – honesty, integrity, visibility, accountability – are used by others to judge their trustworthiness and therefore these can influence their research by affecting the decisions made by all stakeholders. This sub-section draws together these principles, how they interrelate, and their importance for working practices and research achievements when studying complex environmental problems. Figure 21 draws out the principles which emerged from the interviews that an individual researcher can control in the face of uncertainty, alongside techniques used by others to gauge these.

Researchers can be honest, accountable, and provide visibility of the uncertainties in their research and the results. Communication is vital in the assessment of quality control, reproducibility, transparency and collaborations, providing a way for others to judge the ability and integrity of the researchers. Decisions can then be made based upon the perceived trustworthiness, reputation, and credibility of the researcher, potentially providing a means of reducing the uncertainty level of the decision-maker. As highlighted in chapter 5 this is an important aspect of decision-making.

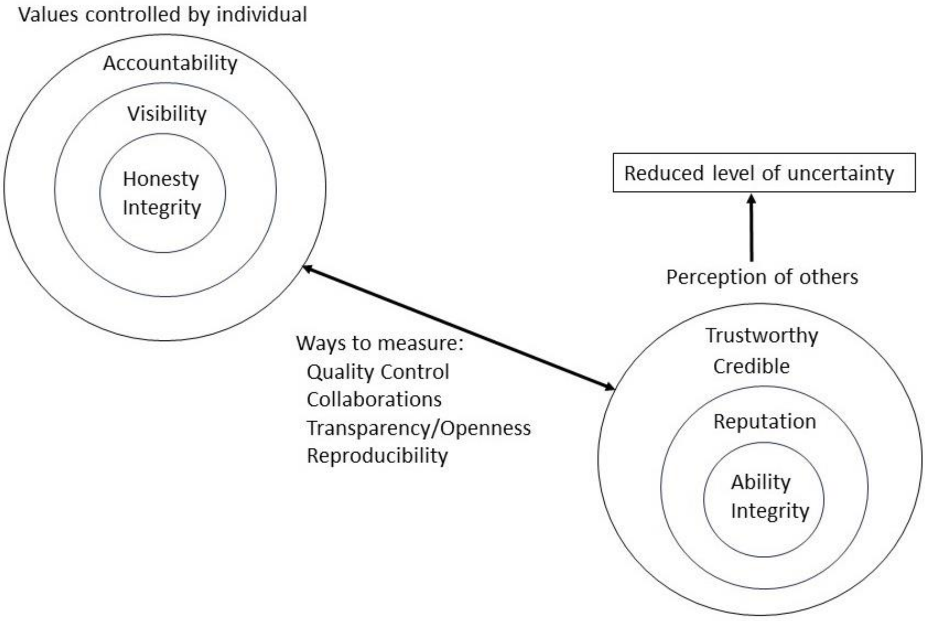

Figure 21. The relationship of an individual's principles and how these affect the perception of the individual by others

7.7 Conclusion

This chapter has built on the tensions and challenges in environmental data science created by collaboration, discussed in chapter 6. Drawing upon the valuable experiences of environmental data science experts associated with CEEDS, it has explored uncertainties in data and analysis and how they are handled. In doing so, the chapter has investigated deeper insights to aid the understanding of the different uncertainties experienced when using data for decisions, introduced in chapters 2 and 3. Challenges relating to data discussed by participants include:

Data availability: there is a large amount of heterogeneous environmental data available, but the chapter has highlighted that the quality of data affects its usability.

Data quality: the availability and quality of metadata emerged as a major problem for environmental data scientists. Many practitioners rely on secondary data so comprehensive metadata is critically important for communicating information about the data. The absence or scarcity of metadata hampers the availability of usable data, necessitates the formulation of assumptions, and affects the quality of analyses. It therefore has a major impact on the production of data-driven evidence for decisions and the level of uncertainty that a user may have about the evidence. Availability, accessibility, usability and metadata can be aided by the use of standards and guiding principles discussed in chapter 3, and the publication of data-related journal papers discussed by P3 and P14. These can provide rigorous quality assurance to show the calibre of data.

Figure 22 summarises the uncertainties identified in this chapter and shows some options for mitigating these, suggested by the interviewees (in the red boxes). These uncertainties are added to the uncertainty typology in the following chapter.

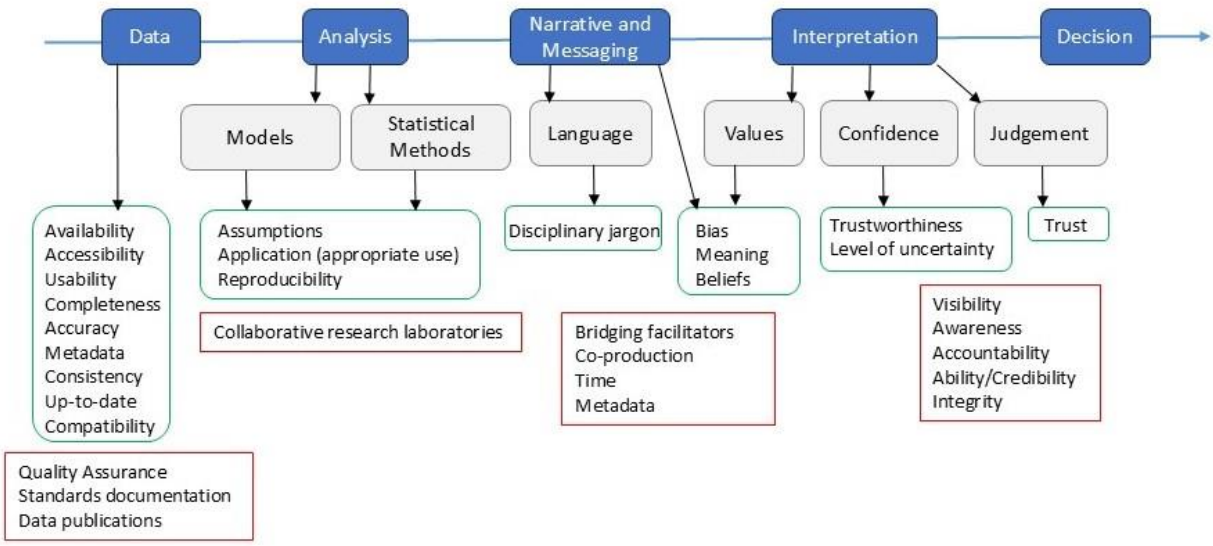

Figure 22. Summary of uncertainties and options for overcoming these resulting from the CEEDS interviews

Collaboration across diverse knowledge-holders presents challenges, but also presents opportunities. Efforts to overcome such problems are being made by those who value cross-disciplinary research, although not all researchers are equally comfortable venturing beyond the confines of their disciplinary boundaries. Ways to move forward include co-production, additional time in projects and 'bridging people' who can facilitate the research across stakeholder boundaries. The incorporation of knowledge from diverse sources can generate areas of ignorance for those operating outside their accustomed subject domains. This creates a reliance on trust based on the competence, reputation, credibility, and trustworthiness of others. While most scientists aspire to uphold trustworthiness and safeguard their reputations, working on policy-relevant science can challenge principles such as honesty, integrity, visibility, and accountability. The perception of these in others is very important when different stakeholders are making decisions along the pathway, affecting their level of uncertainty.

One feature emerging from the three research study chapters is communication of uncertainty – the dilemma of how it should be communicated, what should, or needs, to be communicated and the impact of communicating particular uncertainties – all of which affect the level of transparency, or translucency, of the resulting research. The communication of the quantitative uncertainties relating to the data and analysis provides an objective transparency, providing the impartial communication discussed in chapter 5. However, the communication of qualitative uncertainties could be described as subjective transparency, and as this is not a standard scientific practice these uncertainties often remain opaque. Therefore, in order to improve trust in science the communication of qualitative uncertainties needs to be enhanced and is considered in the communication framework discussed in the following chapter.

This chapter serves as a pivotal bridge between theoretical frameworks and contemporary real-world applications, shedding light on the nuanced interplay between uncertainties, the principles of scientists, and how these effect collaborative efforts within the dynamic landscape of environmental data science. Although post-normal science provides a framework for environmental data science – particularly the need to assess the quality of research and involvement of the extended peer community – the chapter has shown that these elements can present additional challenges.

The following chapter incorporates elements from all the previous chapters to create a new typology of uncertainty for environmental data science, the development of a framework for communicating uncertainty for environmental data scientists and considers the relevance of post-normal science to environmental data science in more detail.

8 Discussion

8.1 Introduction

Complex environmental problems affect many people and require (often-urgent) policy decisions, increasing the requirement for policy-relevant scientific research to provide evidence. Alongside this, application of data science methods to an increasing volume of environmental data has led to the emergence of environmental data science as an important new research area, transforming traditional environmental science research. Furthermore, the drive for open and transparent research has highlighted that there are a variety of uncertainties in scientific research, many of which have not been previously acknowledged, and the impacts of these not considered. The previous chapters have investigated, through literature and through the thoughts and experiences of experts working within environmental domains, these changing requirements for contemporary science. Emerging from these observations are the challenges and opportunities this creates for scientists. To navigate the uncertainties discussed in previous chapters, this chapter contributes insights and tools to assist environmental data scientists with the challenge of providing data-driven evidence for decision-making.

The chapter is divided into three sections:

Section 8.2 draws together the uncertainty literature from chapter 3, and the research chapters 5, 6 and 7, to summarise the uncertainties that affect environmental data science research, and to inform a new typology for uncertainty in environmental data science. The typology highlights the different uncertainties along the data-to-decision pathway that different stakeholders need to navigate to make decisions. In doing so, it provides a key to enable all stakeholders to understand the challenges that others face along this pathway, to reduce tensions when stakeholders work together, and to produce robust decisions.

Section 8.3 pulls together the discussions on the key common feature of all three research studies – communication – to propose a framework that would enable environmental data scientists to communicate the different types of uncertainty more effectively with the different stakeholders. Along with the typology, examples of this framework are provided for the challenges of vegetation monitoring and stratospheric ozone depletion to show how they can be applied.

Finally, section 8.4 considers whether the concept of post-normal science adds value to environmental data science.

8.2 Uncertainty in environmental data science; a new typology

The sources of uncertainty experienced by the participants in the three research studies of this thesis have been assimilated to create a typology of the uncertainties experienced by different stakeholders along the data-to-decision pathway. The pathway consists of many collaborators, from data collector, data analysers, statistical and process modellers, through to the decision-maker themselves. Therefore, setting out the uncertainties in this way enables an understanding of where the different uncertainties arise, who they affect, and how they may compound along the pathway. It is anticipated that this will encourage transparency of the uncertainties to aid the provision of robust scientific evidence to underpin and build trust in environmental decision-making. This typology covers a broader variety of uncertainties than the discipline specific uncertainty typologies discussed in chapter 3, as it also incorporates consideration of uncertainties arising from communication and cognition.

The initial typology was developed from literature reviewed in chapter 3, particularly using the typologies developed by Skinner *et al.* (2014a; 2014b), and then enhanced using the data from the interviews and focus groups discussed in chapters 5, 6 and 7. The typology developed by Skinner *et al.* (2014a; 2014b) (see page 53) provides details on aleatory and epistemic uncertainties in the environmental risk research process and that they feed into decisions, however, the detailed uncertainties that can occur between the two are not discussed. The dimensions of uncertainty proposed by Walker *et al.* (2003) – nature, location (source), level – provide a useful way to interpret the different types of uncertainty. These have been absorbed into this new typology, which is dominated by the sources of epistemic uncertainties. Aleatory uncertainties are included within statistical methods (under statistical theory), and the levels of uncertainty included with confidence.

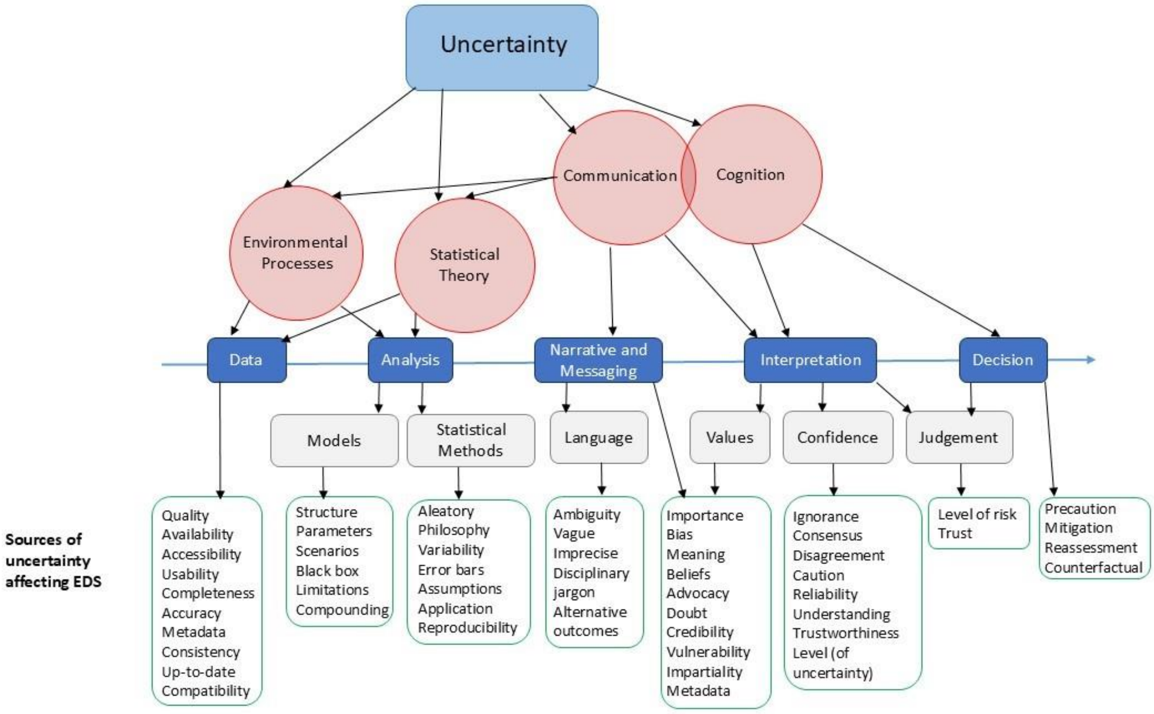

Figure 23. Typology of uncertainty for environmental data science

Introduced in chapter 3, and shown in Figure 23, the new typology divides uncertainty which relates to environmental data science into four main categories:

- **Environmental processes,** which show the uncertainties experienced when research is trying to understand *what* is causing environmental changes.
- **Statistical theory,** which provides a quantitative assessment of uncertainty providing an assessment of the *probability* of an event or environmental change occurring.

- **Communication** includes all uncertainties which relate to any forms of communication between stakeholders, so impacts on the other three categories.

- **Cognition,** which covers any uncertainties relating to the thought processes of stakeholders. In chapter 3 communication and cognition were separate but they are now shown as overlapping as they are heavily reliant on each other.

Figure 23 links these higher-level uncertainties from the literature review to those experienced by the participants taking part in this study. The uncertainties described by interviewees and focus group participants elaborate these categories in relation to environmental data science and are described below using the data-to-decision pathway (see blue pathway on Figure 23). The participants in the DSNE and CEEDS studies provided a rich source of information for the uncertainties associated with the data and analysis sections. Many participants provided experiences relating to communication and interpretation of scientific research. Experience of the participants with decision-makers was more limited. However, some from CEEDS and many involved in the ozone study provided details for this section, and further research with decision-makers is suggested in the Conclusion. Although the wider society and public come up as stakeholders through the thesis specific uncertainties have not been included as they were not part of this study, again another avenue for further research.

8.2.1 Data

Data uncertainties were mainly discussed in the interviews with CEEDS members. A limited number of people in the interview group collected their own data, revealing that one important feature of environmental data science is the reliance on data that others have collected. Although there is a large amount of environmental data collected, finding suitable, **usable,** good **quality** data presents a challenge. As discussed in chapter 3, datasets can be **incomplete** or **inaccurate**, due to problems with instrument availability or calibration, they can be biased, e.g. due to instrument positioning, or **inconsistent**, due to different people collecting the data, such as with field surveys, or **unavailable** due to pragmatic difficulties of data collection – location, cost or time. The development of data centres has increased the **availability** and **accessibility** of data, but the type of datacentre (i.e. open or managed) affects the quality of the data available. Alongside this some data collectors are unwilling to provide access to their data. The major problem discussed by interviewees was the provision of **metadata**, which is used to judge the quality of the data, and therefore affects the usability of data due to a lack of information. Also mentioned in the CEEDS interviews is the new practice of integrating different types of data, which can be problematic due to **incompatibility** of scales or units. Additionally, in order to make decisions it is important that the data is **up-to-date**. However, access to real-time data was not mentioned by any study participants, although it was a source of frustration discussed at a workshop of environmental data scientists attended by the author. One reason for this frustration is because collectors of this type of data are reluctant to release it before some level of veracity checking has taken place, so there is a lag before it becomes available.

The volume of data available provides opportunities for environmental data science, however, it is not always straightforward to use and can affect the level of uncertainty that the researcher feels about results. Sources of epistemic data uncertainty were discussed in chapter 3, section 3.4.1, which are summarised in Skinner *et al.* (2014b) as availability, precision and reliability. This new typology presents an elaboration of these, with reliability affected by the availability of metadata.

8.2.2 Analysis

All these data uncertainties can then affect the quality of the analysis. In the typology, this section is divided into models and statistical methods, although there is some overlap of uncertainties between the two. As discussed in chapter 3, there is a lot of discussion in the academic literature about model uncertainties, such as with model **structure/design**, and input **parameters**. The integration of models raises concerns about how these different model uncertainties may **compound** through the different models. Often the model system is a '**black box**', whereby a user is ignorant of the internal structure. These uncertainties were discussed in the focus group study where concern was raised that they are not sufficiently accounted for, therefore one challenge for environmental data science is to try to quantify the impact of these uncertainties in the results. The use of models to create **scenarios** provides a useful tool for decision-making, however, as they provide a prediction based on assumptions, they are inherently uncertain and not everyone will agree with the outputs. However, although modellers in all the studies recognise that there are **limitations** of models, this is not necessarily communicated to the user of the model outputs, so communication of this should be improved to make it clear that the output is a simulation and may differ from reality.

Turning to statistical methods, the choice of method can influence uncertainty, with the more subjective **philosophy** of Bayesians, discussed in the focus groups, based on experiential **assumptions** of the researcher, which will therefore differ between individuals. As mentioned in chapter 6, statistical methods incorporate **aleatory** uncertainty. Statistical uncertainty includes a quantitative assessment of data **variability** and provision of **error bars**. Also included within this division is **application,** which is to cover the appropriate use of methods and whether the research is **reproducible**, both of which were discussed by CEEDS participants in chapter 7.

8.2.3 Narrative and Messaging

Once the data has been analysed, the resulting outputs will be communicated, whether that is to research colleagues, within a cross-disciplinary project, or to a wider audience. **Metadata** makes an important contribution to this communication as it is also needed on the outputs produced for decision-making and stakeholder communication. Additionally, the communication of **alternative outcomes** (or scenarios) may be necessary when the uncertainties are deep. Covered by many of the study's participants, the collaborative, and often, transdisciplinary nature of environmental data science can create problems with **language** and understanding of **disciplinary jargon**. This could be due to **ambiguity** where the same terminology is used to mean different things, leading to misunderstanding, or from the use of **imprecise** or **vague** terms. Sometimes this is intentional, as mentioned by one participant in chapter 7, to skew, or **bias**, a narrative leading to an ambiguous interpretation. If this is not the case, then the message to be communicated needs to be considered thoughtfully, as described in chapters 5 and 7, so that the message, or **meaning**, being portrayed is interpreted in the way the communicator intends. This prevents the scientist isn’t **vulnerable** from being misinterpreted and remains **credible**. However, this division overlaps with aspects of cognitive uncertainty, introducing behavioural uncertainty and an individual’s **values** and **beliefs**, which can affect how results are presented and received, or even whether any uncertainties are communicated at all. As discussed in chapter 5, scientists often with to remain **impartial** so they are not accused of **advocacy**. Uncertainties created by this reception, or interpretation, of the narrative are continued in the following section.

8.2.4 Interpretation

The interpretation of uncertainty as a lack of knowledge, when presented to non-academics was discussed by study participants, showing that the results being communicated are not always **understood**, creating a route for those wishing to create **doubt**. In the typology, interpretation is split into values, confidence and judgement. The **values** or beliefs of stakeholders affect their interpretation and judgement of evidence. **Confidence** reflects the **level of uncertainty** and is the personal confidence of the researcher in the methods or the data they used, or the confidence of other stakeholders in the results (relating to **reliability** and **trustworthiness**). This is also affected by their **trust** in either the process of production or the producer of the results. All of these can impact on the potential **consensus,** or **disagreement,** about the environmental processes taking place. The deeper areas of **ignorance** or unknowns, discussed in chapters 2 and 3, are also included in this division.

8.2.5 Decision

All these uncertainties can affect an individual's judgement and the decisions that they make, with some more important than others. Alongside this, the decision-maker has their own values and beliefs, other criteria that they need to consider, as well as deciding on the **level of risk** of taking a particular **mitigating** action or even no action. A decision-maker could take **precautionary** action if the level of risk is high. Although this step appears at the end of the pathway, it is not the end of the decision process, as it is likely that this will be iterative with the decision/s **reassessed** and the **counterfactual** considered, as discussed in chapter 5. This fits into an adaptive process to allow for revision of a decision in light of new information.

Methods currently used by the IPCC to communicate scientific uncertainty were discussed in chapter 3, i.e. the use of likelihood and confidence. However, these assess the probability so relate to quantitative uncertainties. It could be argued that better communication of the qualitative uncertainties would provide additional information to mitigate and raise awareness of unknowns for making decisions. Use of this uncertainty typology would aid a more holistic communication and understanding.

8.3 Communication of uncertainty

Tensions due to communication emerged as a key finding from this research. It is one of the most problematic aspects for the environmental data scientists that participated in this study. Whether this is a lack of communication, misinformation, misunderstanding, or misinterpretation - all of which can create a barrier to navigating uncertainty in environmental data science. Improved communication between scientists and decision-makers would increase transparency/translucency, reducing levels of uncertainty and aiding decision-making.

8.3.1 A communication framework

A framework is proposed (Table 11) to aid environmental data scientists with communicating uncertainty, formulated from elements of the typology and findings from the research studies discussed in chapters 5, 6 and 7. Other frameworks for communicating uncertainty are available, e.g. NUSAP (Funtowicz and Ravetz, 1990) and objects of uncertainty (van der Blaes *et al.*, 2019), discussed in chapter 2. However, this framework is more specific to environmental data science and aims to encourage environmental data scientists to think about how to communicate uncertainties to non-disciplinary stakeholders.

One key feature that came out of the study is the need to consider the recipient/s of the communication and the aspects of uncertainty that they need to know, also noted by Fischhoff and Davis (2014). To summarise, the communication problems experienced by the participants in the studies were:

Disciplinary colleagues: communication of metadata, assumptions and methods used.
Cross-disciplinary collaborations: interpretation problems due to language or terminology ambiguities or different perspectives.
Other non-academic stakeholders: consideration of their background knowledge; what do they need to know; presentation of research to prevent misinterpretation or loss of message.

This framework could be used for communicating both quantitative and qualitative uncertainties but emphasises qualitative uncertainties that would otherwise remain hidden but can aid interpretation of quantified uncertainty. It therefore provides a means of improving visibility of these uncertainties to other stakeholders.

Table 11. Proposed framework for uncertainty communication

Stakeholder	**Potential source of uncertainty**				
Audience? (what do they need to know?)	Data	Analysis	Message (could include risk of event)	Interpretation (is evidence understandable & level of event impact included)	Decision (could include counterfactual)
Disciplinary colleague					
Colleague from another discipline/data user unrelated to project					
Funder					
Decision-maker					
Other stakeholder					

Alongside consideration of stakeholder, the framework includes potential sources of uncertainty, taken from the typology, where communication problems could arise – data, analysis, message, interpretation, decision – although not all these will be relevant to all stakeholders. The data and analysis columns are relatively straightforward and should include any of the uncertainties listed in the typology that are relevant. The message column can prompt thought about what exactly the researcher is wanting to portray, and the best way to get this across, e.g. possibly by the use of risk to show the impact, as discussed in chapter 5. Interpretation links with message, to make sure that the research is understandable to the particular audience and that the message portrayed will be interpreted correctly. Within this, it may be useful to convey the level of confidence or uncertainty that the researcher has in the results, if these could impact on a decision. Finally, the decision column could include any judgements made, decision reflections or actions to be communicated.

While discussing this framework with some CEEDS interviewees (P5, P12, P14) to consider examples for the following section it was clear that scientists don't think about the bigger uncertainty picture that this aims to portray. One interviewee (P12) said that this framework made them think differently about communicating the uncertainties as they had not considered the more qualitative aspects. Once the audience has been established then the communicator can consider the most appropriate means of communication. Various ways of presenting and communicating uncertainty have been discussed through the thesis. To summarise, some options that could or should be considered and tailored to the audience include:

- Metadata (especially for disciplinary colleagues/data users)
- Quantified uncertainty, e.g. probability, error bars, etc
- Relevant visualisation methods, e.g. graphs, maps
- Additional qualitative information to aid interpretation of quantified uncertainty
- Clarity of terminology (especially for non-disciplinary stakeholders/decision-makers)
- Storylines which put the risks and impacts into perspective

- Traffic light system to indicate severity

This framework should be used in conjunction with the uncertainty typology proposed in the previous section, together providing a useful tool for environmental data scientists to think about and convey uncertainties to all stakeholders along the data-to-decision pathway. Two examples of the use of this tool are provided in the following section. A more detailed exploration of the practicability of this tool provides an avenue for future research.

8.3.2 Application of the typology and framework

The two thesis outputs – the typology and communication framework – have been applied to two examples of environmental challenges to show how they can be used. These applications are stratospheric ozone depletion and a national vegetation monitoring scheme. The information for a national vegetation monitoring scheme example has been provided by interviewees from the CEEDS research study (P5, P14). The stratospheric ozone depletion example is based on the literature and interview information from chapter 5.

The ozone depletion phenomenon started with a hypothesis that the Earth's protective ozone layer could be affected due to human activities. Initially these activities were hypothetical and had not been defined, and evidential data for any ozone destruction was not available. In the early days simple models were used to simulate the possible effects, for which there would have been many uncertainties and limitations. Analysis of data collected from ground-based instruments and satellites was slow, thought to be inaccurate and there was minimal inter-disciplinary collaboration. However, the potential impacts on human health from ultra-violet radiation from the sun were sufficient to initiate precautionary legislative decisions. Figure 24 shows the typology adapted to consider the uncertainties associated with the early stages of the ozone depletion challenge (green box) and those which emerged over time (orange box). As discussed in chapter 5, as research progressed different uncertainties arose, so the use of this tool needs to be iterative. Once the available data was analysed and researchers realised that the theories of ozone layer destruction had become a reality with the finding of the Antarctic ozone hole, research and global legislative action erupted. Many decisions needed to be made, large amounts of funding become available, many more stakeholders became involved, multi-disciplinary research was required, all contributing to many of the communication challenges discussed in this thesis.

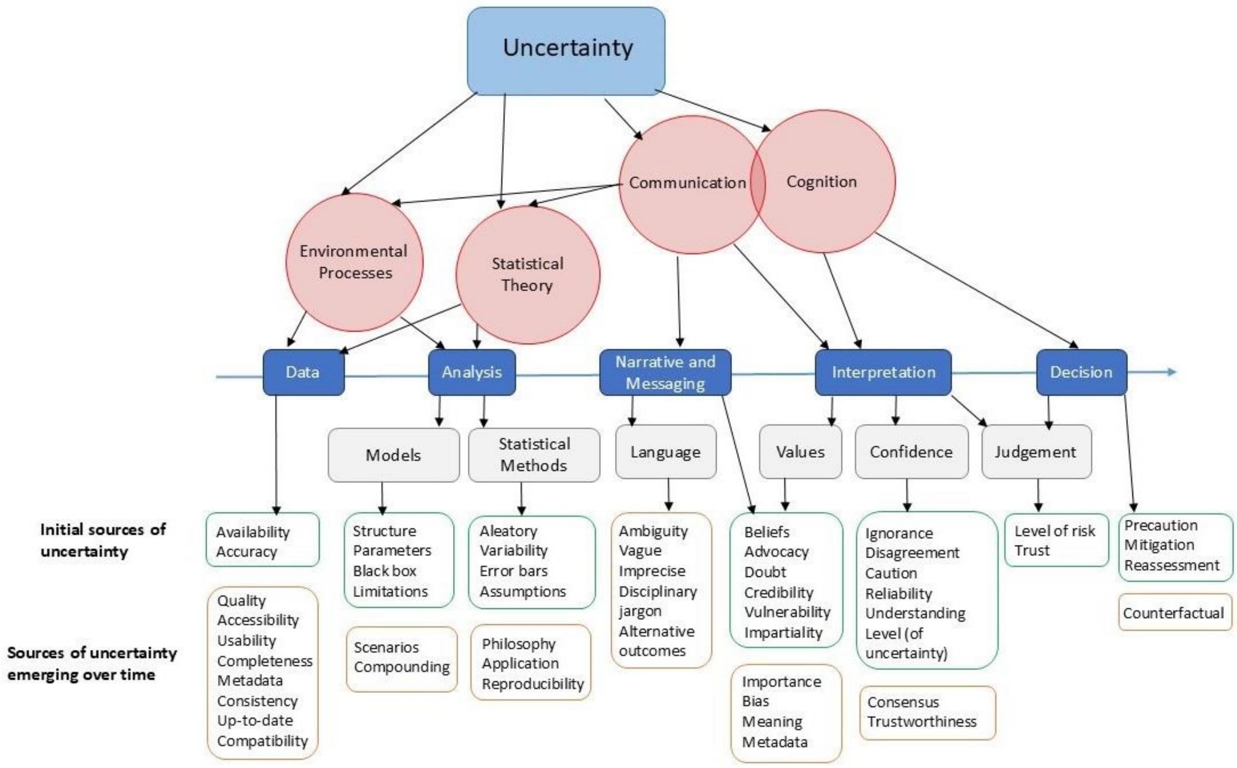

Figure 24. Example typology of uncertainties experienced for ozone depletion

The communication framework shown in Table 12, provides an example of some communication uncertainties for ozone depletion as the phenomena was unfolding. This incorporates the emerging challenges mentioned above as this environmental problem developed from theory to reality, and along the pathway from data to decision. Initially, uncertainties to be discussed with disciplinary colleagues would involve reducing ignorance. Research was urgently required to understand the causes and the extent of the problem – the environmental processes taking place, data to be collected, what instrumentation needed to be developed, locations for research – all uncertainties which then needed to be communicated to the research funders and decision-makers. This high level of ignorance was accepted and incorporated into the legislative process, with a four-yearly review of research and respective updates to legislation.

Table 12. Example framework for uncertainty communication for stratospheric ozone depletion

Stakeholder	**Potential source of uncertainty**				
Audience?	***Data***	***Analysis***	***Message***	***Interpretation***	***Decision***
Disciplinary colleague	Instrument calibration Instrument failure Availability of suitable instruments to measure additional chemicals Satellite data collected but not looked at No data at all for certain locations Many areas of ignorance	Aleatory uncertainty (noise) No prediction of ozone reduction over Antarctica Little data to verify models	Faulty data Not enough data What data needs collecting and how – ground, satellite, aircraft, balloons	Quicker analysis of available data to assess extent of ozone depletion More data required to find out why	Need field campaigns to obtain data – how, who, where? New instruments need to be developed
Colleague from another discipline/data user unrelated to project	Lots of ignorance Sparsity of data available in early days	Global problem so requires global research collaboration	Needs interaction between disciplines – chemists, physicists, meteorologists	Which disciplines need to respond? Availability of scientists with relevant background?	Who to trust to collaborate with?
Funder	Not enough data Don't know mechanisms	Lots of ignorance	Limited knowledge about the problem, urgent need for more research	Urgent requirement for research funding - Cost - Time - Resources	Panel/s of experts needed to develop and review research strategy (who) Research needs to be coordinated to prevent duplication of effort (how) Call for proposals to undertake research
Decision-maker			Ozone layer protects the Earth from sun	Risk to human health of no action - urgent action required? Global problem so requires global legislative action Need to take precautionary action	Need for precautionary action National & global legislation needed 4-yearly scientific reviews to alleviate uncertainties Consider scenarios of continual CFC release (counterfactual)
Other stakeholder	Thinning of ozone layer – why?	(industry) denial that CFCs causing problem (doubters) reasons?	(public) Health problems due to increased UVB from sun Threat to Earth's protective shield by CFCs	If don't take action then lots more people globally will get skin cancer Everyone can take action (i.e. stop using aerosols)	(industry) Development of substitutes (media) Encourage reduction in aerosol use

The application of the typology and communication framework to the national vegetation monitoring scheme provides a contemporary example. The long-term monitoring of vegetation enables comparison with previous surveys, providing evidence for vegetation changes and used to develop policies for management of the countryside.

Figure 25 shows the uncertainties that arise along the pathway for this example. Data uncertainties particularly relate to accuracy and consistency as the data is collected by human observations. Accuracy is therefore dependent on the competency of the surveyor. As data is collected over a long period of time access to plots and changes of personnel impact data consistency. A handbook of guidelines for vegetation surveyors is provided to standardise procedures. However, this does not mitigate for the capability of an individual surveyor, but this uncertainty would only be communicated between colleagues (see Table 13). A sample of plots are audited by an independent assessor to produce QA reports which are made available to stakeholders.

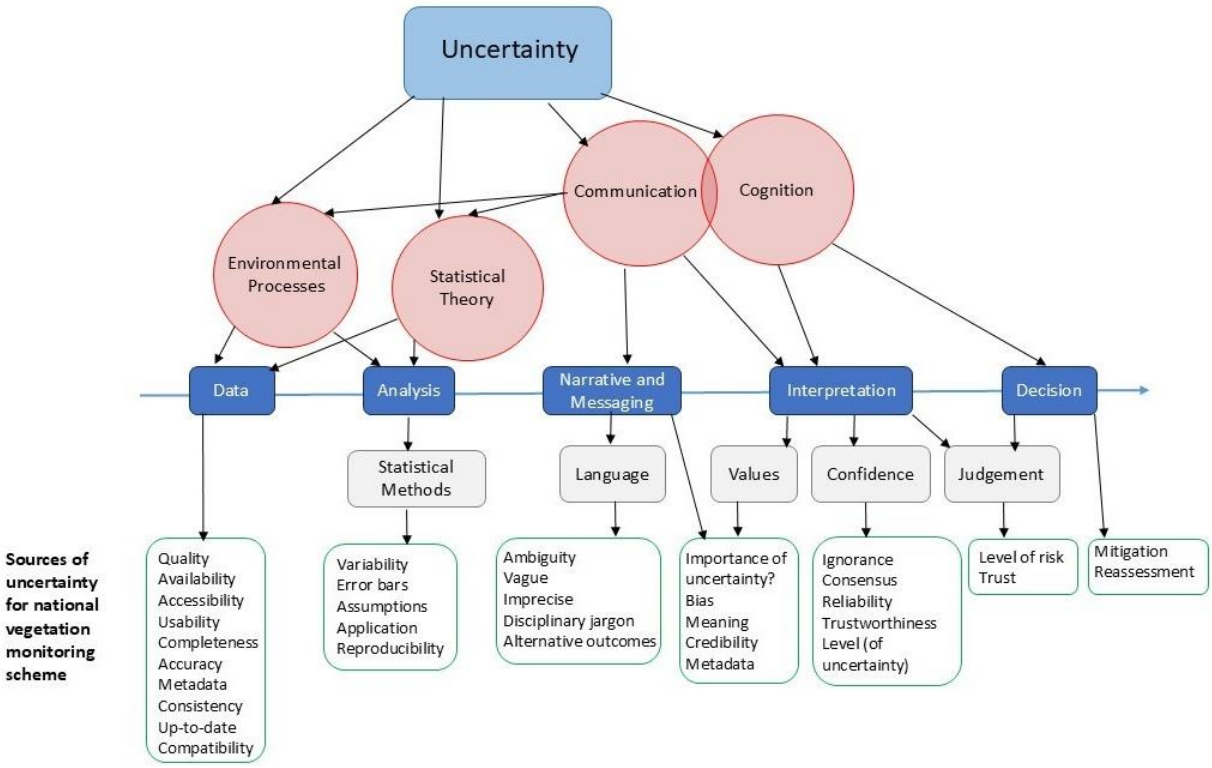

Figure 25. Example typology of uncertainties experienced for a national vegetation monitoring scheme

The data can be accessed under licence via a managed data repository and detailed metadata is included for anyone wanting to reuse the data. However, some information is not disclosed, such as the location of survey plots which remain confidential to protect the landowner and to prevent sabotage. This, however, could present a problem to the data user if they wish to combine this data with another dataset and is therefore an uncertainty that they should communicate with their analyses.

Technical reports are available via a dedicated website which provide details on sampling and statistical analysis procedures. Scientific analyses are provided in journal publications. Reports detailing the results and comparisons to previous surveys are available via the internet, but little detail about uncertainties are included. Headline results are simplified into a short glossy report for non-experts. Apart from some quantitative uncertainties mentioned in the technical and QA reports, uncertainties are not provided as standard procedure, signalling that the communication of uncertainty is less important to the researchers for this context.

For this example, risks to human health are not high and decisions are less urgent, so although this would indicate an example of normal science, there are many people interested in this data and it is used for decision-making.

Both these two examples of the typology include some similar uncertainties to those noted by Skinner *et al.* (2014a) discussed in chapter 3. The similarities relate to data, analysis, consensus and language. However, the examples included in this section add more detail about the human-related uncertainties, particularly relating to reliability, credibility and therefore trust in others. These impact on uncertainties relating to communication and decision-making, relating to confidence or levels of uncertainty that others feel about scientific evidence. Inclusion of these aspects make this new typology relevant for environmental data science, and aid its establishment as an important new discipline for the production of policy-relevant scientific evidence.

Table 13. Example framework for uncertainty communication for a national vegetation monitoring scheme

<table>
<tr><th>Stakeholder</th><th colspan="5">Potential source of uncertainty</th></tr>
<tr><td>Audience?</td><td>Data</td><td>Analysis</td><td>Message</td><td>Interpretation</td><td>Decision</td></tr>
<tr><td>Disciplinary colleague</td><td>Accuracy
Completeness
Non-native species
Missing species
Missing/inconsistent data, e.g. if permission denied to access repeat plots
Handbook for surveyors</td><td>Uncertainties/errors provided by statistical analysis
Bias-corrections
Independent QA
Initial sense check of data
Re-analysis of data
Modelling requires additional assumptions about the distribution of data</td><td>Low/high recording of specific vegetation species in comparison to previous surveys</td><td>Data collection errors/invalid data (relating to capability and therefore trust of surveyor/s)
Or consider why changes are occurring (e.g. invasive species?)</td><td>Extensive QA analyses to see if data from specific surveyors need to be removed
Other reasons for changes seen.
Future considerations – additional training, rigorous recruitment, quality vs quantity of plots</td></tr>
<tr><td>Colleague from another discipline/data user unrelated to project</td><td>Locations are confidential
Data available via data repository
Data requires licence to access
Sampling strategy document</td><td>Lineage:
Data processing methods
Supporting documentation (inc. Handbook for surveyors) available via data repository</td><td>Restricted access to site information to preserve the integrity of sites and goodwill of landowners
Detailed metadata available</td><td>Some metadata needs to remain confidential</td><td>Restrictions could impact useability of data for requirements of some users</td></tr>
<tr><td>Funder</td><td colspan="2" rowspan="2">No specific detail about data & analysis uncertainties, apart from that provided in:
Technical reports – statistical report includes some uncertainties
QA Reports and Analysis (available via website)</td><td>Comprehensive QA carried out therefore risk of poor data has been mitigated</td><td>Satisfied that research provides information required</td><td>Report can be circulated and publicised</td></tr>
<tr><td>Decision-maker</td><td>As above and potential reasons for why any changes have occurred</td><td>Decrease in plant diversity</td><td>Management policy required?
Risks of no action e.g. loss of species/speed of spread of species/impact</td></tr>
<tr><td>Other stakeholder</td><td>(landowner) Policy for access to land</td><td>None</td><td>(public) Glossy report presenting simplified objective results</td><td>Headline statistics provided on web – no specific details of any uncertainties</td><td>Context – does it matter? Or which uncertainties matter?</td></tr>
</table>

8.4 Environmental data science and post-normal science

The crux of tackling contemporary environmental challenges is the provision of understandable and trustworthy policy-relevant scientific outputs to provide evidence for decision-making. However, these are often fraught with high levels of uncertainty, are open to differing opinions and often require urgent decisions, making the post-normal science framework relevant for science production in these circumstances. As the remit of environmental data science is to provide data-driven evidence for decisions, then the two main tenets of post-normal science – quality control and inclusion of an extended peer community – which enable judgement on the scientific evidence provided, are relevant to this emerging discipline. However, this thesis has shown that in practice these requirements can create tensions and push scientists into situations that can make them uncomfortable, particularly once they move away from the normal research within their disciplinary boundaries with which they are familiar.

A major feature of a post-normal environmental problem is that it affects many people and therefore there are many potential stakeholders who would like to have input. Environmental challenges still rely on normal, single disciplinary, applied science, to analyse data and provide scientific evidence, but they also require the incorporation of knowledge from other academic disciplines and from non-academic stakeholders, allowing integration of all types of knowledge into the decision-making process. Transdisciplinary research projects involve people from different disciplinary backgrounds, alongside community representatives, funders, and decision-makers, which can create problems with understanding each other, particularly regarding the use of terminology. However, if the participants have a shared understanding of the end goal, then there are ways to overcome these problems. Cross-disciplinary collaborations can be beneficial and the input from different knowledge sources can answer different questions and push research boundaries further. However, it takes a certain mindset to see the benefits of the extra effort this type of research requires, as it is time consuming, and some people are not prepared to do it. Reflecting on the CEEDS interviewees, most of these were positive about working in a cross-disciplinary way, however, it should be acknowledged that as members of the interdisciplinary CEEDS, they are likely to have a positive bias towards this mode of research.

Cross-disciplinary collaborations require a trusting relationship between project partners. Participants in this study were conscious of being trustworthy, and maintaining their credibility, so that others will trust their work. Reputation provides a way for others to judge this, which can be ascertained via the quality of research. Transparency of uncertainties, sharing data, and providing metadata, can support research quality and ultimately, the challenge is to get people to work differently and to see the value of these aspects of research. Some CEEDS interviewees (P3, P13) discussed how they felt that mindsets needed to change, to stop pushing back against post-normal scientific changes, particularly regarding being more open with their data, their science or to working with researchers from other disciplines. Some described this as “cultural” differences (CEEDS P5, P6), but really these are scientists who wish to continue to do their research within the bounds of ‘normal’ science and are unwilling to embrace the changes needed for policy-relevant science. One reason for this reluctance is differing philosophies, with some scientists preferring to remain within the realist ontology and positivist epistemology. This study has shown that those more open to collaboration follow a pragmatic realist approach, with a realist ontology and interpretivist epistemology. Under normal science the need to be transparent about their uncertainties is reduced, the scientists can hide behind the scientific method and the perceived objectivity of science and are judged upon their peer-reviewed publications.

Societal expectations of science since the concept of post-normal science was proposed add additional pressures to contemporary scientific research. The increasing democratisation of science, discussed in chapter 2, has led to a questioning of scientific evidence. For example, the post-truth mindset creates doubt and a lack of trust in science. This presents problems for scientists who work at the boundary of science and policy. As discussed in chapter 5, some scientists try to remain impartial, not expressing their personal views in order to maintain their credibility, particularly relevant in the current ‘post-truth’ age. With credibility, their research is seen as trustworthy and the evidence they are presenting can be relied upon for making decisions. The potential interpretation of uncertainty as 'not knowing' (as discussed in chapters 5 and 6) makes scientists reluctant to acknowledge uncertainty, as this could also damage credibility. However, as discussed in chapters 5 and 7, the principles, values and viewpoints of scientists are rarely disclosed, potentially impacting on the message being presented, so although transparency is advocated for trustworthy science, in reality these aspects remain opaque.

Once the uncertainties become too deep, described as ignorance in the original post-normal framework (see Figure 2, in chapter 2), the decision options become limited. This has precipitated the use of precaution, but other decision tools are becoming available and could be considered. Therefore, the new methods proposed which incorporate review and adaptation, such as those proposed in chapter 2 as Decision Making under Deep Uncertainty, should be used to recognise and mitigate ignorance (see Figure 26). Environmental data science methods can aid with this as data becomes available.

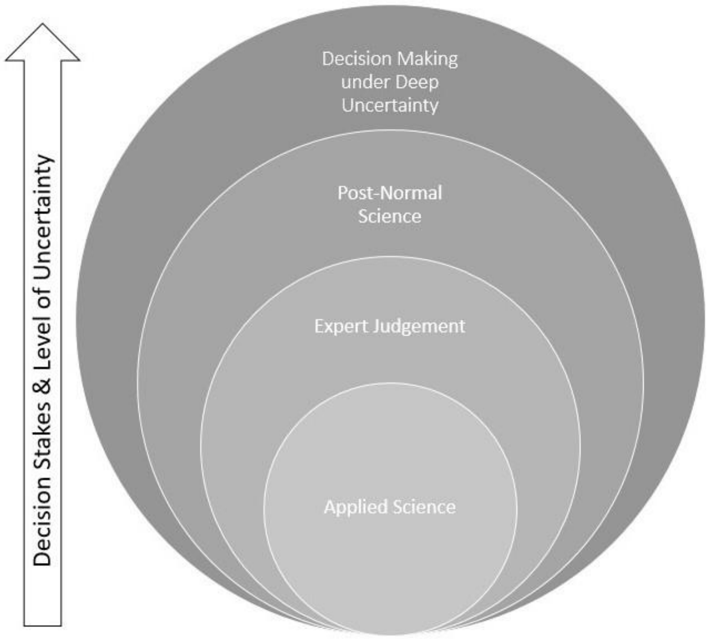

Figure 26. An alternative to ignorance for contemporary environmental research, adapted from Figure 2

The post-normal science concept provides a framework for the production of policy-relevant science and is therefore a relevant concept for environmental data science.

However, the production of scientific evidence for decision-making is not always straightforward and other factors, such as improving communication between stakeholders and developing alternative ways to communicate uncertainty, also need to be considered.

8.5 Conclusion

This discussion chapter has drawn together the previous chapters to discuss three different aspects of the research:

Section 8.2 synthesises the insights gained from the uncertainty literature explored in chapter 3 and the research findings from chapters 5, 6 and 7, to develop a new typology for understanding the different uncertainties affecting environmental data science. This typology serves as a valuable tool for researchers and practitioners in this field, enabling them to understand the uncertainties, experienced by the different stakeholders, arising along the pathway from data to decision. It is anticipated that with better understanding of each other's perspectives, common ground will be easier to find, enabling research to progress.

Section 8.3 brings together the theme of communication, which emerged as a common thread in all three research studies. Effective communication of uncertainty is paramount for environmental data scientists to bridge the gap between their research findings and informed decision-making. A framework is proposed for communicating uncertainty, emphasising the need to consider the audience for communication and their requirements. This has been applied to two examples to show how it can be used to provide a way to identify sources of communication uncertainty within environmental challenges. Although these examples are for quite different environmental challenges, with different data collection methods (instrumentation vs. human) and different scales (global vs national) they show that many of the uncertainties experienced are similar.

Section 8.4 considers whether post-normal science provides a useful framework for environmental data science. This perspective acknowledges the complexities and interplay of science, policy, and societal values in decision-making processes related to the environment and highlights the challenges these present.

This discussion chapter encapsulates the dynamic and evolving nature of environmental data science. It underscores the vital role that this emerging subject area plays in addressing complex environmental issues, and highlights the importance of transparency of uncertainties, the challenge of embracing post-normal science principles, and the need to enhance communication strategies to meet the challenges of the future.

9 Conclusion

This chapter concludes this study. It provides a summary of the thesis (9.1), a review of the research questions (9.2), the contributions to research (9.3), some potential avenues for future research (9.4) and a final concluding paragraph (9.5).

9.1 Thesis summary

This thesis has provided an in-depth review of the uncertainties to be navigated by environmental data scientists when providing scientific evidence for decision-making.

Chapter 2 situated uncertainty within scientific research literature, drawing out the changing relationship between science, society, and policy decision-making. The increasing need for global environmental decision-making over the past 50 years has motivated scientific practices to change in response to the uncertainty of the situation, providing a foundation for the necessity of this study. Depending on the type of uncertainty, decisions can be based on risk if it can be quantified, but if ignorance abounds then different decision options must be considered, such as precautionary action or the more contemporary practice of adaptive decision methods. The increasing influence of society, along with societal expectations, affects the acceptability of these decision methods over time, to the extent that trust in science is perceived to have been eroded. The concept of post-normal science was suggested in the 1980s which incorporates additional methods to mitigate this, which focus on quality control and transdisciplinarity, and is still relevant today. The use of data-driven evidence to back up decisions has created new opportunities for academic study, culminating in the emergence of environmental data science as a new subject area. This focus on the use of data for making decisions creates a pathway from the collection of the data to the decisions made. However, as highlighted by this thesis, moving along the pathway is dependent on many people with many different skills and knowledge.

Chapter 3 focused on the different types of uncertainty, highlighting the complexity of this concept, and the different definitions provided in the literature. Concepts relevant to environmental data science were identified, with those from environmental risk literature particularly relevant, especially the dimensions of uncertainty identified by Walker et al. (2003) of nature, source, and level. This review of multidisciplinary literature on uncertainty enabled the initial development of the data-to-decision uncertainty pathway. It showed that the uncertainties could be divided between those associated with environmental processes, statistical theories, communication and cognition, creating the top level for developing a typology of uncertainty for environmental data science. The cognitive impact of uncertainty, e.g. an individuals' understanding and the level of certainty they feel about research results, have a major impact on the decisions to be made.

Chapter 4 explained the research studies that comprise this PhD, the methods used and how the different studies fit together. Environmental data science is a collaborative, and often transdisciplinary, discipline. The different research methodologies between scientific and social scientific research are explored in this chapter, providing a reason for tensions when these types of research are combined.

Chapter 5 presented a case study which looked at the historical problem of stratospheric ozone depletion. This longitudinal study combined literature and interviews to explore the handling of uncertainties over time. Initially, there was little data evidence, so legislation promoted use of the Precautionary Principle for decision-making before more data was collected to provide proof. This was one of the first environmental problems requiring global legislation, propelling scientists' involvement at the science-policy boundary - the study found that some are not comfortable with this and wish to remain impartial to the environmental cause to maintain their credibility. Additional insights from this chapter include suggestions for the understandable communication of uncertainty, which focused on describing risks and counterfactuals, which could be incorporated into contemporary environmental data science.

Chapter 6 presented the analysis of transcripts from focus groups held with data scientists from the collaborative DSNE project. Drawing on their statistical and quantitative backgrounds the chapter provided an understanding of the specific meaning of statistical uncertainty, which to some authors discussed in the literature review was the only definition of uncertainty. Alongside this, the chapter discovered sources of confusion and tension which can occur when different disciplines collaborate, such as differing philosophies and understanding of disciplinary language. Problems with communication – people's understanding of uncertainty and how to communicate with non-specialists – also emerged from these focus groups.

Chapter 7 presented the analysis of semi-structured interviews conducted with members of CEEDS, a group of environmental data scientists from different environmental sub-disciplines. This chapter delved deeper into a wider range of uncertainties all along the data-to-decision pathway, focusing particularly on uncertainties associated with collecting primary data and the problem of availability of metadata for using secondary data, which can affect the quality of research results. Emerging from these interviewees is the aspiration to be trustworthy, and consideration of how they place trust in others so that they do not damage their reputation. Principles of honesty, integrity, visibility, and accountability can aid these; however, they can be challenged when working on policy-relevant science. The perception of these in others is very important when different stakeholders are making decisions along the pathway.

Chapter 8 combined aspects of all the previous chapters to develop a new typology of uncertainty for environmental data science. This aids navigation of uncertainty along the data-to-decision pathway for all stakeholders. Alongside this, a framework for the communication of uncertainty for environmental data scientists is proposed, and has been applied to two environmental challenges. This chapter also considered the relevance of the post-normal science framework to environmental data science. It is argued that, although the features of quality control and inclusion of all stakeholders are still very relevant, societal expectations since the development of this concept require evolution of PNS to replace decision-making options under ignorance with new adaptive methods of 'decision-making under deep uncertainty', to incorporate evidence from data as it becomes available.

9.2 Revisiting the research questions

Changes occurring in the natural environment are complex, often interrelated and affect many people. The mitigation of these environmental challenges requires policy intervention; urgent decisions need to be made based on a variety of knowledge sources and opinions. Central to this is scientific research, to provide evidence for the reasons for change, alongside the potential impacts and solutions. However, scientific methods and practices have been critiqued by social scientists, who have highlighted that scientific research is not as certain as often portrayed. Additionally, the relationship between science, society, and policy has evolved significantly leading to an expansion of stakeholders, alongside a questioning of scientific evidence and the expertise of scientists. Moreover, journal retractions, scientific fraud and a new sensibility — post-truth — is enabling a perception of the erosion of trust in scientific evidence. The uncertainty of scientific research is often used to delay decisive actions so environmental problems intensify. However, the increasing availability of environmental data and use of alternative analysis techniques from statistics and computing are providing data-driven evidence for environmental decision-making. This is creating a paradigm shift for environmental studies, leading to the emergence of environmental data science as a new discipline.

This study has presented a synthesis of multidisciplinary literature on the use of scientific knowledge for decision-making and on uncertainty, to identify relevant features for environmental data science, along with the inductive, thematic analysis of interviews and focus groups with environmental data scientists, to answer the following research questions:

RQ1: What are the different types of uncertainties experienced along the data-to-decision pathway, and how do these uncertainties influence environmental data science research used for making decisions?

Uncertainty is a complex concept. The analysis of multidisciplinary literature reveals that it has many different meanings and understandings, which themselves also contribute to a person's level of certainty. Further exploration of uncertainty through interviews and focus groups provided more in-depth information about how environmental data scientists experience uncertainty. The use of data to provide evidence for decision-making creates a data-to-decision pathway onto which these different uncertainties can be mapped. These relate to sources of uncertainty in primary and secondary data, analysis, messaging of results and interpretation, alongside the different levels of cognitive uncertainty that stakeholders may feel. Therefore, the uncertainties range from quantitative, relating to any data used, through to qualitative, relating to individual stakeholders.

Due to the collaborative nature of environmental data science, and therefore the number of different people involved along the pathway, there are different uncertainties which affect individuals differently. Data-driven evidence is perceived by some as objective and therefore any decisions made based on this data are assumed to be without any human bias. However, this thesis has shown that many aspects of research are based on human decisions, and even the seemingly objective statistical methods don't provide impartial results. Although researchers advocate transparency, many aspects remain opaque, potentially creating additional uncertainty.

RQ2: What methods are currently used to navigate uncertainty, and what are the other techniques that could be adopted to enable an improved passage though uncertainty for decision-making?

Analysis of the interview and focus group data collected for this study examined the research practices of environmental data scientists used to navigate uncertainties to produce trustworthy scientific results. Quantification of data uncertainty is an established method using statistical techniques and enables a decision-maker to consider the probability (and therefore risk) of taking particular actions. However, once uncertainty is not quantifiable then other methods need to be established. For example, the consensus of experts to produce scientific assessments is an established method to present the current status of knowledge to decision-makers. Such an assessment, to be undertaken every four years, was incorporated into the Montreal Protocol legislation as a way of acknowledging the uncertainties in the science of stratospheric ozone depletion.

The cross-disciplinary nature of environmental research is a source of tension. However, environmental data science tools are developing to overcome this, such as digital collaborative research environments. Other methods to mitigate some of the tensions of cross-disciplinary research emerged from the study, including the use of 'bridging' people within a research project to facilitate disciplinary language and expectation barriers, and to aid communication and understanding. A key finding of this research relates to difficulties of communication, both within cross-disciplinary research groups but also for the presentation of results. A communication framework has been developed to aid environmental data scientists' communication of uncertainty, particularly focussing on what the audience needs to know. Improvements to the communication of uncertainty will enhance the transparency of research, reduce misunderstandings, and enable stakeholders to establish the quality of the scientific results. Alongside this, as decisions rely heavily on the perception of others, improved communication will enable stakeholders to ascertain the integrity and credibility of each other. All of these factors can contribute to the reduction of cognitive uncertainty.

RQ3: Can an examination of historical environmental challenges and concepts that have evolved over the past 50 years yield valuable insights that can be harnessed to propel environmental data science into the future?

Initially, science was about discovery and offered an illusion of certainty. However, increasing environmental complexities highlighted the need for new approaches, leading to the emergence of "post-normal science" in the 1980s. This approach integrates scientific knowledge with policymaking, recognising that traditional, or 'normal', scientific methods were insufficient in the face of unquantifiable uncertainties. Core features of this concept are the use of quality control to assess the scientific results, and the inclusion of all the people who have a stake in the environmental problem.

These features, investigated and elucidated through this thesis, enable the creation of trustworthy scientific evidence, and resonate with the aims of environmental data science. However, this thesis has revealed that the addition of these features can add further uncertainties and challenges to the scientific process.

The ozone depletion study confirmed the uneasy relationship between science and policy when scientists are pushed out of their academic norms, described by Jasanoff (1994). The study revealed that many scientists are reluctant to blur the lines between science and policy, they wish to remain impartial so that they cannot be accused of adding any political bias to their scientific messaging and are able to maintain their credibility. By maintaining credibility the scientists are trusted, their science is perceived as trustworthy, and their research can therefore have impact on decision-making. This study also proposed two alternative ways to portray uncertainty which can be incorporated into the communication of contemporary environmental problems. One proposal was the importance of translating uncertainty into risk so that potential environmental impacts are apparent. Statistical uncertainty is used to show the probability of events, which could be used to show the risk of occurrence in a particular location. Representing uncertainty in these ways make it more relatable and so engaging stakeholders in more informed decision-making. The other suggestions was to provide the counterfactual to decision-makers, so they are aware of the alternative outcomes if different decisions were made.

9.3 Contributions

This thesis has made the following important contributions to aid improvement of environmental data science research:

- *It has provided a deeper understanding of the many different uncertainties in environmental data science research that are to be navigated by the different stakeholders associated with a particular environmental problem.*

The complexity, along with different meanings and understandings, of uncertainty creates a challenge for researchers working in environmental data science. Many typologies of uncertainty have been proposed for different disciplines but do not cover the wide range of uncertainties experienced by participants in this study. Building on these, this study has created a new typology of uncertainty for environmental data science increasing transparency of the uncertainties experienced. By setting out the different types of uncertainty along a data-to-decision pathway stakeholders are able to understand how these uncertainties affect other stakeholders working at different points of the pathway. Moreover, understanding the uncertainties navigated by others will aid transdisciplinary research by enabling groups to reach common ground more quickly and understand reasoning behind decisions made.

- *It has revealed the challenges and tensions of environmental data science associated with the necessity for people from different backgrounds to work together and trust each other.*

The collaborative and transdisciplinary nature of environmental data science enables this discipline to provide evidence for complex environmental decisions. This dependence on others requires trust and the study has shown that the researchers are conscious of being trustworthy, and producing results which can be trusted by others. The impact on the scientists of carrying out research which feeds into policy is rarely discussed. This study found that in order to be trustworthy researchers were conscious of remaining impartial, thereby maintaining their credibility and reputation. Therefore, although quantitative transparency is advocated as a means to overcome some uncertainties, as noted in the study many qualitative aspects of research remain opaque.

- *It has discovered that communication of uncertainty is a key concern to researchers and improving this is vital for making robust decisions based on data-driven evidence.*

The dilemmas of how uncertainty should be communicated, what should be or needs to be communicated and the impact of communicating particular uncertainties, emerged as problematic for the environmental data scientists. All of these affect the level of transparency, or translucency, of the resulting research, and consequently the level of trust that stakeholders have in the evidence provided and the decisions they are able to make. A framework for the communication of uncertainty for environmental data science is presented in this thesis to prompt thought into who the audience is and what uncertainty information they require. Providing too much information, or too little, can be a source of confusion (or uncertainty) preventing decisions to be made.

9.4 Future research

This thesis has opened up several avenues for future research:

<u>Uncertainty communication</u>

How to communicate uncertainty is clearly a problematic aspect of environmental data science, and finding ways to improve this has emerged as critical for the future of this discipline. Further exploration of this topic would be beneficial for environmental data scientists communicating with each other and with decision-makers. A more in-depth investigation of current techniques from other disciplines reported in academic literature (c.f. van der Blaes *et al*., 2019) would provide practical insights, including further exploration of the use of risk, as suggested by the interviewees in chapter 5. Qualitative research methods (interviews, focus groups and workshops) would be important to further develop the experiences of environmental data scientists in this area. Alongside this, such methods should be used with research users to establish what techniques they have found understandable and useful. An addition to this would be to further explore with environmental data science practitioners and stakeholders whether the communication framework suggested in chapter 8 is applicable, and where it can be further developed and improved.

<u>The uncertainty of decision-makers</u>

The interviewees in this study provided conflicting perspectives on their experiences of communicating uncertainty with decision-makers. The stereotypical image is that decision-makers do not understand uncertainty. However, actuality appears to be much more nuanced. It would be helpful to expand the current study to include a decision-makers perspective on how uncertainty affects the decisions they make and how the types of information they are given helps or hinders this process. This could also include an investigation into whether they are aware of, or interested in, all the different types of uncertainty appearing along the data-to-decision pathway.

Tensions of cross-disciplinary research

The rise of, and reliance on, cross-disciplinary research creates an interesting area to study. In-depth mixed methods research into the use of inter-, multi- and trans-disciplinary research could be used to explore how these different types of collaboration work in practice. As discussed in this thesis, differing cultures and mindsets can be a source of tension, so it would be interesting to delve into these further and investigate whether other challenges arise when conducing this type of research. It could establish whether attitudes to this mode of research are changing with the increasing desire of research funders to promote and fund cross-disciplinary research. Additionally, an investigation into whether the objective/subjective (philosophical) dilemma does have an impact on how people from different disciplines work together, would add impact to claims for additional time to be allocated to cross-disciplinary research projects.

Credibility in science

Establishing and maintaining credibility has emerged as important to scientists from this study, so further investigation into this, and other tacit principles of scientists, could provide further insights to this aspect of scientific research production. Semi-structured in-depth interviews with scientists to look specifically at credibility, reputation and impartiality would be interesting, along with consideration of whether there are factors which affect this, e.g. discipline, stage of career or demographic factors. Related to this would be to explore whether the opaqueness of scientists' benefits, or is detrimental to, science and the drive for openness and transparency.

9.5 Concluding Remarks

This thesis was motivated by the requirement to understand how uncertainty influences decision-making in environmental research. The growing reliance on data-driven evidence for decision-making has led to the emergence of the new discipline of environmental data science. This discipline depends on the collaborative efforts of experts from various fields to gather, analyse, and interpret data to inform decisions. However, uncertainties arise throughout this process—both quantitative, related to data and analytical methods, and qualitative, concerning the individuals involved—posing significant challenges to the research process. As scientific techniques continue to advance, environmental data science will be increasingly called upon to provide answers. This thesis highlights the current challenges experienced by environmental data scientists and provides valuable insights to help propel the field forward.

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Appendix A. Ethics Application

Faculty of Science and Technology Research Ethics Committee (FSTREC)

Lancaster University

Application for Ethical Approval for Research

This form should be used for all projects by staff and research students, whether funded or not, which have not been reviewed by any external research ethics committee. If your project is or has been reviewed by another committee (e.g. from another University), please contact the FST research ethics officer for further guidance.

In addition to the completed form, you need to submit **research materials** such as:

i. Participant information sheets
ii. Consent forms
iii. Debriefing sheets
iv. Advertising materials (posters, e-mails)
v. Letters/emails of invitation to participate
vi. Questionnaires, surveys, demographic sheets that are non-standard
vii. Interview schedules, interview question guides, focus group scripts

Please note that **you DO NOT need to submit pre-existing questionnaires or standardized tests** that support your work, but which cannot be amended following ethical review. These should simply be referred to in your application form.

Please submit this form and any relevant materials **by email as** a **SINGLE attachment** to *fst-ethics@lancaster.ac.uk*

Section One

Applicant and Project Information

Name of Researcher: Katherine Wright

Project Title: Understanding how stakeholders derive valid and actionable decisions from data science in the face of uncertainty

Level: PhD

Supervisor (if applicable): Bran Knowles & Gordon Blair

Researcher's Email address: k.wright@lancaster.ac.uk

Address: B086/B087, Science and Technology Building, Lancaster University

Names and appointments/position of all further members of the research team: n/a

Is this research externally funded? NO If yes, ACP ID number:

Funding source:

Grant code:

Does your research project involve any of the following?

þ Human participants (including all types of interviews, questionnaires, focus groups, records relating to humans, use of internet or other secondary data, observation etc.)

☐ Animals - the term animals shall be taken to include any non-human vertebrates or cephalopods.

þ Risk to members of the research team e.g. lone working, travel to areas where researchers may be at risk, risk of emotional distress

☐ Human cells or tissues other than those established in laboratory cultures

☐ Risk to the environment

☐ Conflict of interest

☐ Research or a funding source that could be considered controversial

☐ Social media and/or data from internet sources that could be considered private

☐ any other ethical considerations

Yes – complete the rest of this form

No – your project does not require ethical review or submission of this form

Section Two

Type of study

X Includes direct involvement by human subjects. **Complete all sections apart from Section 3.**

Involves *existing documents/data only*, or the evaluation of an existing project with no direct contact with human participants. ***Complete all sections apart from Section 4.***

If your research involves data from chat rooms and similar online spaces where privacy and anonymity are contentious, please complete all sections

Project Details

1. Anticipated project dates (month and year)

Start date: November 2019 **End date:** March 2023

2. Please briefly describe the background to the research (no more than 150 words, in lay-person's language):

Research in environmental sciences uses a large amount of data and along with analytical methods there are many areas where uncertainties can occur. These can be due to either the randomness of world (e.g. the future is not known) or due to knowledge limitations. This project is a mixed methods study to look at uncertainties in environmental data, and how stakeholders deal with these when making decisions. It is part of the Digital Science of the Natural Environment project, so environmental data relating to this project will be considered along with a historical issue for comparison.

3. Please state the aims and objectives of the project (no more than 150 words, in lay-person's language):

The aims of the project are to understand the uncertainties faced and the decision-making process that stakeholders have to consider in order to make sure that the results are robust. In particular participant interviews will lead to a greater understanding of:

- What are the sources of uncertainty in the data, methods and analysis that stakeholders face;
- How the stakeholder deals with these uncertainties;
- What influences the decisions that they have to make;
- How decisions are communicated;
- Changes in uncertainties and decision-making over the past 30-40 years.

4. Methodology and Analysis:

I will carry out semi-structured interviews and focus groups with stakeholders in order to understand their experiences of uncertainty and decision-making in the field of environmental science. Participants will be recruited from scientific organisations, universities, UK research councils – typically with established collaborations with Lancaster University and/or the student.

Each interview and focus group will last for roughly one hour. The interviews and focus groups will be audio recorded and transcribed by the student. Audio recordings and transcriptions will be stored in a secure, encrypted folder on a computer; personal data will be confidential and kept separate from participant responses. In instances where the participant's role is relevant to the publication, they will not be named without express signed consent from the participant.

<u>Section Three</u>

Secondary Data Analysis n/a

Complete this section if your project involves *existing documents/data only*, or the evaluation of an existing project with no direct contact with human participants

1. Please describe briefly the data or records to be studied, or the evaluation to be undertaken.

2. How will any data or records be obtained?

3. Confidentiality and Anonymity: If your study involves re-analysis and potential publication of existing data but which was gathered as part of a previous project involving direct contact with

human beings, how will you ensure that your re-analysis of this data maintains confidentiality and anonymity as guaranteed in the original study?

4. What plan is in place for the storage of data (electronic, digital, paper, etc)? Please ensure that your plans comply with the General Data Protection Regulation (GDPR) and the (UK) Data Protection Act 2018.

5. What are the plans for dissemination of findings from the research?

6a. Is the secondary data you will be using in the public domain? YES/NO

6b. If NO, please indicate the original purpose for which the data was collected, and comment on whether consent was gathered for additional later use of the data.

7.What other ethical considerations (if any), not previously noted on this application, do you think there are in the proposed study? How will these issues be addressed?

8a. Will you be gathering data from discussion forums, on-line 'chat-rooms' and similar online spaces where privacy and anonymity are contentious? YES/NO

If yes, your project requires full ethics review. Please complete all sections.

<u>Section Four</u>

Participant Information

Complete this section if your project includes *direct* involvement by human subjects.

1. Please describe briefly the **intended human participants** (including number, age, gender, and any other relevant characteristics):

The intended participants will include about 50-60 adults who are academics, researchers, policymakers/influencers who are currently, or recently retired from, working in role related to environmental data science. Age, gender and other demographics are not relevant factors of analysis.

2. How will participants be **recruited** and from where?

Participants will be recruited using professional contacts (e.g. those connected to the DSNE project), contacts recommended by Supervisors or other interviewees or are personally known to the researcher. Participants will be invited to participate by e-mail.

3. Briefly describe your **data collection methods**, drawing particular attention to any potential ethical issues.

I will conduct semi-structured, mainly one-to-one, interviews and focus groups with participants. They will be to be audio recorded and transcribed by myself. A set of questions will be drafted in advance based on the project aims, with regard to decisions they have made or have knowledge about.

As the subject matter is not necessarily confidential, prior consent from the interviewee will be obtained as to whether they wish to remain anonymous or are happy to named. I will check again at the end of the interview or focus group in case anything arose that they would prefer to remain confidential.

4. Consent

4a. Will you take all necessary steps to **obtain the voluntary and informed consent** of the prospective participant(s) or, in the case of individual(s) not capable of giving informed consent, the permission of a legally authorised representative in accordance with applicable law? **YES**

If yes, please go to question 4b. If no, please go to question 4c.

4b. Please explain the procedure you will use for **obtaining consent**?. If applicable, please explain the procedures you intend to use to gain permission on behalf of participants who are unable to give informed consent.

I will provide Participant Information Sheets and Consent Forms for all interviewees and focus group attendees, and will talk through these materials with participants when collecting signatures on consent forms. I will also ensure that participants are aware of when the audio recording equipment is on.

4c. If it will be necessary for participants to take part in the study **without their knowledge and consent at the time**, please explain why (for example covert observations may be necessary in some settings; some experiments require use of deception or partial deception – not telling participants everything about the experiment). Not applicable.

5. Could participation cause **discomfort** (physical and psychological eg distressing, sensitive or embarrassing topics), **inconvenience or danger beyond the risks encountered in normal life**? Please indicate plans to address these potential risks. State the timescales within which participants may withdraw from the study, noting your reasons.

I do not anticipate any stress caused by this study – other than the potential disruption caused by setting aside time to participate in the study. For this reason, interviews and focus groups will fit with the timescales of the interviewee. To appropriately mitigate any discomfort that may arise during or following participation, participants will be able to withdraw from the study at any time before or during the interview/focus group and up to six weeks following their interview/focus group.

6. How will you protect participants' **confidentiality and/or anonymity** in data collection (e.g. interviews), data storage, data analysis, presentation of findings and publications?

Interview/focus group transcriptions will be stored securely on One Drive, and will only be available to myself. The participants will be able to see the text where they are named before publication or thesis submission. If an interviewee has requested to remain anonymous, all their data will remain anonymous, and they will not be identifiable in any project outputs: I will anonymise any direct quotations which may be used in the reports or publications from this study.

7. Do you anticipate any ethical constraints relating to **power imbalances or dependent relationships**, either with participants or with or within the research team? If yes, please explain how you intend to address these? None anticipated.

8. What potential **risks may exist for the researcher** and/or research team? Please indicate plans to address such risks (for example, noting the support available to you/the researcher; counselling considerations arising from the sensitive or distressing nature of the research/topic; details of the lone worker plan you or any researchers will follow, in particular when working abroad.

Interviews/focus group will be conducted on the Lancaster University campus or at other institutions. In the case of any off-campus face-to-face interviews, I will inform my supervisors of the name the participant I will be meeting along with the date, time and location of the meeting, and will check in with my supervisors after the meeting.

9. Whilst there may not be any significant direct **benefits to participants** as a result of this research, please state here any that may result from participation in the study.

There is unlikely to be any direct benefit to the participants, however, participation will allow interviewees to share their experiences and issues with working with environmental data. Their feedback may be beneficial at a future date, as their contribution may provide greater clarity to the issues.

10. Please explain the **rationale for any incentives/payments** (including out-of-pocket expenses) made to participants: Not applicable

11. What are your plans for the **storage of data** (electronic, digital, paper, etc.)? Please ensure that your plans comply with the General Data Protection Regulation (GDPR) and the (UK) Data Protection Act 2018.

Data will be collected using an encrypted recording device. Personally identifiable information will not be collected, and all data will be stored on an encrypted password-protected laptop, and on One Drive. Hard copies of Personal Information Sheets and Consent Forms will be stored securely in a locked cabinet at Lancaster University and will be destroyed once the thesis is written.

12. Please answer the following question *only* if you have not completed a Data Management Plan for an external funder.

12.a How will you make your data available under open access requirements?

Data will also be deposited in Lancaster University's institutional data repository and made freely available with an appropriate data license.

12b. Are there any restrictions on sharing your data for open access purposes?

Due to the small sample size and the nature of the questions and the participants' unique knowledge, even after full anonymization there is a risk that participants can be identified. Therefore, supporting data will only be shared on request with genuine researchers. Access will be granted on a case by case basis by the Faculty concerned.

13. Will **audio or video recording** take place? ☐ no þ audio ☐ video

13a. Please confirm that portable devices (laptop, USB drive etc) will be **encrypted** where they are used for identifiable data. If it is not possible to encrypt your portable devices, please comment on the steps you will take to protect the data.

The portable devise will be encrypted, but it is anticipated that audio recordings will be transferred to One Drive as soon as possible following the interviews. Once the interviews /focus groups have been transcribed the recordings will be deleted.

13b. What arrangements have been made for **audio/video data storage**? At what point in the research will tapes/digital recordings/files be destroyed?

All audio recordings will be deleted from the recording device once transferred onto an encrypted laptop and One Drive.

13c. If your study includes video recordings, what are the implications for participants' anonymity? Can anonymity be guaranteed and if so, how? If participants are identifiable on the recordings, how will you explain to them what you will do with the recordings? How will you seek consent from them?

14. What are the plans for dissemination of findings from the research? If you are a student, mention here your thesis. Please also include any impact activities and potential ethical issues these may raise.

The main dissemination of findings will be my PhD thesis. Results of the research may be submitted for publication in an academic/professional journal and/or at relevant conferences and workshops.

15. What particular ethical considerations, not previously noted on this application, do you think there are in the proposed study? Are there any matters about which you wish to seek guidance from the FSTREC? None

Section Five

Additional information required by the university insurers

If the research involves either the nuclear industry or an aircraft or the aircraft industry (other than for transport), please provide details below:

Section Six

Declaration and Signatures

I understand that as Principal Investigator/researcher/PhD candidate I have overall responsibility for the ethical management of the project and confirm the following:

- I have read the Code of Practice, Research Ethics at Lancaster: a code of practice and I am willing to abide by it in relation to the current proposal.
- I will manage the project in an ethically appropriate manner according to: (a) the subject matter involved and (b) the Code of Practice and Procedures of the University.
- On behalf of the University I accept responsibility for the project in relation to promoting good research practice and the prevention of misconduct (including plagiarism and fabrication or misrepresentation of results).
- On behalf of the University I accept responsibility for the project in relation to the observance of the rules for the exploitation of intellectual property.
- If applicable, I will give all staff and students involved in the project guidance on the good practice and ethical standards expected in the project in accordance with the

University Code of Practice. (Online Research Integrity training is available for staff and students here.)

- If applicable, I will take steps to ensure that no students or staff involved in the project will be exposed to inappropriate situations.
- I confirm that I have completed all risk assessments and other Health and Safety requirements as advised by my departmental Safety Officer.

þ Confirmed

Please note: If you are not able to confirm the statement above please contact the FST Research Ethics Committee and provide an explanation.

Student applicants:

Please tick to confirm that you have discussed this application with your supervisor, and that they agree to the application being submitted for ethical review ☒

Students must submit this application from your Lancaster University email address, and copy your supervisor in to the email in which you submit this application

All Staff and Research Students must complete this declaration:

I confirm that I have sent a copy of this application to my Head of Department (or their delegated representative). Tick here to confirm ☒
Name of Head of Department *(or their delegated representative)* Professor Adrian Friday

Applicant electronic signature: Kate Wright Date 25.10.19 (amendment 24.05.21)

The following pages form part of this application but are provided separately for ease of reference.

Appendix B. Participant information sheet (Interviews)

For further information about how Lancaster University processes personal data for research purposes and your data rights please visit our webpage: www.lancaster.ac.uk/research/data-protection

I am a Research Student at Lancaster University and I would like to invite you to take part in my research about 'Decision-making in the face of uncertainty in environmental science'.

Please take the time to read the following information before you decide whether or not you wish to take part.

What is the study about?

Research in environmental sciences uses a large amount of data and along with analytical methods there are many areas where uncertainties can occur. These can be due to either the randomness of world (e.g. the future is not known) or due to knowledge limitations. This project will look at uncertainties in environmental data, and how stakeholders deal with these when making decisions. It is part of the Digital Science of the Natural Environment project, so environmental data relating to this project will be considered along with a historical issue for comparison.

Why have I been invited?

I have approached you because I am interested in the views of a wide range of stakeholders in this domain. I believe your knowledge in the area and your views will be valuable to my study.

What will I be asked to do if I take part?

If you decide to take part, this will involve participating in a semi-structured interview lasting roughly one hour.

What are the possible benefits from taking part?

If you take part in this study, your insights will contribute to the understanding of uncertainty and decision-making in environmental data. This would be beneficial to the research community in terms of knowledge gained.

Do I have to take part?

No. It's completely up to you to decide whether or not you take part. Your participation is voluntary, and you are free to withdraw at any time before, during or within six weeks of the interview, without giving any reason.

What if I change my mind?

You are free to withdraw any time prior to the interview and up to 6 weeks after taking part in the study, and I will extract any data you contributed to the study and destroy it. However, it is difficult and often impossible to take out data from one specific participant when this has already been anonymised or pooled together with other people's data.

What are the possible disadvantages and risks of taking part?

There are no foreseen risks or disadvantages to taking part, apart from volunteering your valuable time in participating in the interview or focus group.

Will my data be identifiable?

After the interview, only myself and my supervisors will have access to the data you share with me. I will keep all personally identifiable information about you confidential, that is I will not share it with others, unless you agree to be named in any dissemination. I will anonymise any audio recordings and hard copies of any data.

How will my data be stored?

Your data will be stored in encrypted files (that is no-one other than me and my supervisors will be able to access them) and on password-protected computers. I will keep data that can identify you separately from non-personal information (e.g. your views on a specific topic).

How will we use the information you have shared with us and what will happen to the results of the research study?

I will use the data you have shared for academic purposes only, to include in my PhD thesis and any academic publications or presentations that arise from this study. When writing up the findings from this study, I would like to reproduce some of the views and ideas you shared with me. When doing so, if you have requested to remain anonymous I will only use anonymised quotes (e.g. from the interview with you), so that although I may use your exact words, you cannot be identified in any publications. If you agree to be named, by signing the relevant section on the consent form, I will attribute any quotes I use by name. I will send any publications to you prior to submission.

Who has reviewed the project?

This study has been reviewed and approved by the Faculty of Science and Technology Research Ethics Committee.

What if I have a question or concern?

If you have any queries or if you are unhappy with anything that happens concerning your participation in the study, please contact:

Kate Wright, k.wright@lancaster.ac.uk**,** B086/B087, Science and Technology Building, Lancaster University, Lancaster, LA1 4WA.

Or one of my supervisors:

Bran Knowles, Department of Computing and Communications, Lancaster University Lancaster, LA1 4WA. E-mail: b.h.knowles1@lancaster.ac.uk

Gordon Blair, Department of Computing and Communications, Lancaster University Lancaster, LA1 4WA.

E-mail: g.blair@lancaster.ac.uk

And if you have any concerns or complaints that you wish to discuss with a person who is not directly involved in the research, you can also contact:

Adrian Friday, Head of Department, School of Computing and Communications, InfoLab21, Lancaster, LA1 4WA. E-mail: a.friday@lancaster.ac.uk

For further information about how Lancaster University processes personal data for research purposes and your data rights please visit our webpage: www.lancaster.ac.uk/research/data-protection.

Thank you for your participation in this project.

Appendix C. Consent Form (Interviews)

Project Title: PhD -Decision-making in the face of uncertainty in environmental science

Name of Student: Kate Wright Email: k.wright@lancaster.ac.uk

Please initial box

☐ **1.** I confirm that I have read and understand the information sheet for the study. I have had the opportunity to consider the information, ask questions and have had these answered satisfactorily.

☐ **2.** I understand that my participation is voluntary and that I am free to withdraw at any time, without giving a reason. If I withdraw within six weeks of the commencement of the study my data will be removed.

☐ **3.** I understand that any information given by me may be used in future reports or presentations by the researchers, but my personal information will not be included.

☐ **4a**. I am happy for my name, my organisations name, or an affiliated association, to appear in any dissemination of the project. **OR**

☐ **4b.** I wish to remain anonymous and understand that my name, my organisations name, or any personally identifiable data will not appear in any dissemination of the project.

☐ **5.** I agree to the interview being audio recorded, and I understand that the interview will be transcribed, and that data will be protected on encrypted devices and kept secure.

☐ **6.** I agree to take part in the above study.

_________________________ _______________ _________________

Name of Participant Date Signature

I confirm that the participant was given an opportunity to ask questions about the study, and all the questions asked by the participant have been answered correctly and to the best of my ability. I confirm that the individual has not been coerced into giving consent, and the consent has been given freely and voluntarily.

Signature of Researcher /person taking the consent ________________________________

Date _____________________ (DD/MM/YYYY)

One copy of this form will be given to the participant and the original kept in the files of the researcher at Lancaster University

Appendix D. E-mail to recruit interview participants

Dear [name],

I am a PhD student at Lancaster University looking at Decision-making in the face of uncertainty in environmental science. The aims of the project are to understand the uncertainties faced and the decision-making process that stakeholders have to consider in order to make sure that the results are robust. In particular, participant interviews will lead to a greater understanding of:

- What are the sources of uncertainty in data, methods and analysis that stakeholders face;
- How the stakeholder deals with these uncertainties;
- What influences the decisions that they have to make;
- How decisions are communicated;
- Changes in uncertainties and decision-making over the past 30-40 years.

As part of this project, I wish to interview a range of stakeholders to help understand the above objectives. The interview will be semi-structured and will not last for more than one hour.

I greatly appreciate taking the time out of your schedule to participate in my research. If you are interested in taking part in my study, or need any more information regarding my project, please do not hesitate to contact me.

Kind Regards,

Kate Wright

Appendix E. Indicative interview questions

Author - Interview Question pointers for the Ozone Study and the CEEDS Study

Please could you tell me/us a bit about your work?

What are the sources of uncertainty in the data, methods and analysis that you have faced?

How did you deal with these uncertainties?

What influenced the decisions that you made?

In your experience, have uncertainties caused any problems?

How have the decisions you made been communicated?

Have you seen a change in the way that uncertainties have been dealt with, and consequently the way decisions have been made over the past 30-40 years? (this question will not be relevant to all participants).

Any other thoughts that would like to add?

Indicative interview questions

L. Thornton- Interview Question pointers for the CEEDS Study

Draft Interview Questions:
Could you tell me about the environmental data you use? What types of environmental science?
Do you predominantly use primary or secondary sources of data, or a combination of both?
What are the predominant issues you face with the data you use?
Do you use data for research or are you more involved with archival/curation?
Have you ever thought about trust in relation to your use of data?
Have you ever considered the impacts that data can have on results?
What springs to mind when you think about: trusting data, and trustworthy data?
What springs to mind when you think about: not trusting data, and untrustworthy data?
Thinking about having trust in data: in what ways do you come to this position? E.g. is there anything in particular you look for?
Have you ever had the experience of getting or collecting data and not trusting it?
Picking out different elements of trust in data - do you have any thoughts on:

- Quality?
- Accuracy?
- Traceability?
- Discoverability?
- Uncertainty?

Are there any current mechanisms you utilise to ensure trustworthy data? E.g. get it from particular places or look for particular things within it?
What would you need or like to see as mechanisms to trust data? E.g. Meta-data/Additional information?

Introduce concept of collaborative research environments if applicable to case.
In your line of work/research do you feel any need for such an environment?
What key characteristics do you feel it would need to have?
Do you feel this would benefit your work with environmental data? In what ways?
Do you think this would help with the predominant issues you outlined with data?
Do you feel that this would be beneficial to having trust in data and trustworthy data?
And finally, is there anything else that you feel we have not discussed?

Thank you.

***Please note that as the interviews were semi-structured not all questions were asked**

Appendix F. Focus group schedule

Aim of group is to discuss uncertainty and to gain an understanding of what it means to the group and how they deal with it.

Start:

Welcome

Introduction to the purpose of the session.

Questions to ask (aim for open-ended questions to aid discussion):

- Introduce themselves and their research area.
- What does uncertainty mean to them (in their work/discipline)?
- Why is it important? (Or even is it important?)
- How do they handle uncertainties?
- Does uncertainty change when working in an interdisciplinary context? (any changes to language used?)
- Have they seen any change over time/career to how uncertainty is discussed/handled? (depending on time)

Reflection on discussion:

- See if they have any further thoughts or want to discuss anything else about uncertainty that’s not been covered.

Thank the group for their time, etc.

Appendix G. Participant information sheet (Focus Group)

For further information about how Lancaster University processes personal data for research purposes and your data rights please visit our webpage: www.lancaster.ac.uk/research/data-protection

I am a Research Student at Lancaster University and I would like to invite you to take part in my research about 'Understanding how stakeholders derive valid and actionable decisions from data science in the face of uncertainty.

Please take the time to read the following information before you decide whether or not you wish to take part.

What is the study about?

Research in environmental sciences uses a large amount of data and along with analytical methods there are many areas where uncertainties can occur. These can be due to either the randomness of world (e.g. the future is not known) or due to knowledge limitations. This project will look at uncertainties in environmental data, and how stakeholders deal with these when making decisions. It is part of the Digital Science of the Natural Environment project, so environmental data relating to this project will be considered along with a historical issue for comparison.

Why have I been invited?

I have approached you because I am interested in the views of a wide range of stakeholders in this domain. I believe your knowledge in the area and your views will be valuable to my study.

What will I be asked to do if I take part?

If you decide to take part, this will involve participating in a focus group lasting roughly one hour. The focus group will take place online (via Microsoft Teams) or on the Lancaster University campus, if face-to-face meetings are allowed/and convenient for the participants, at the time of the focus group. The session will be audio recorded.

What are the possible benefits from taking part?

If you take part in this study, your insights will contribute to the understanding of uncertainty and decision-making in environmental data. This would be beneficial to the research community in terms of knowledge gained.

Do I have to take part?

No. It's completely up to you to decide whether or not you take part. Your participation is voluntary, and you are free to withdraw at any time before, during or within six weeks of the interview, without giving any reason.

What if I change my mind?

You are free to withdraw any time prior to the focus group and up to 6 weeks after taking part in the study, and I will extract any data you contributed to the study and destroy it. However, it is difficult and often impossible to take out data from one specific participant when this has already been anonymised or pooled together with other people's data.

What are the possible disadvantages and risks of taking part?

There are no foreseen risks or disadvantages to taking part, apart from volunteering your valuable time in participating in the interview or focus group.

Will my data be identifiable?

After the focus group, only myself and my supervisors will have access to the data you share with me. I will keep all personally identifiable information about you confidential, that is I will not share it with others, unless you agree to be named in any dissemination. I will anonymise any audio recordings and hard copies of any data.

How will my data be stored?

Your data will be stored in encrypted files (that is no-one other than me and my supervisors will be able to access them) and on password-protected computers. I will keep data that can identify you separately from non-personal information (e.g. your views on a specific topic).

How will we use the information you have shared with us and what will happen to the results of the research study?

I will use the data you have shared for academic purposes only, to include in my PhD thesis and any academic publications or presentations that arise from this study. When writing up the findings from this study, I would like to reproduce some of the views and ideas you shared with me. When doing so, if you have requested to remain anonymous I will only use anonymised quotes (e.g. from the focus group), so that although I may use your exact words, you cannot be identified in any publications. If you agree to be named, by signing the relevant section on the consent form, I will attribute any quotes I use by name. I will send any publications to you prior to submission.

Who has reviewed the project?

This study has been reviewed and approved by the Faculty of Science and Technology Research Ethics Committee.

What if I have a question or concern?

If you have any queries or if you are unhappy with anything that happens concerning your participation in the study, please contact:

Kate Wright, k.wright@lancaster.ac.uk**,** B086/B087, Science and Technology Building, Lancaster University, Lancaster, LA1 4WA.

Or one of my supervisors:

Bran Knowles, b.h.knowles1@lancaster.ac.uk, Department of Computing and Communications, Lancaster University Lancaster, LA1 4WA.

Gordon Blair, g.blair@lancaster.ac.uk, Department of Computing and Communications, Lancaster University Lancaster, LA1 4WA.

And if you have any concerns or complaints that you wish to discuss with a person who is not directly involved in the research, you can also contact:

Adrian Friday, Head of Department, School of Computing and Communications, InfoLab21, Lancaster, LA1 4WA. E-mail: a.friday@lancaster.ac.uk

For further information about how Lancaster University processes personal data for research purposes and your data rights please visit our webpage: www.lancaster.ac.uk/research/data-protection.

Thank you for your participation in this project.

Appendix H. Consent Form (Focus Group)

Project Title: ***PhD* -** Understanding how stakeholders derive valid and actionable decisions from data science in the face of uncertainty

Name of Researchers: Kate Wright Email: k.wright@lancaster.ac.uk

Please read the following carefully:

1. I confirm that I have read and understand the information sheet for the above study. I have had the opportunity to consider the information, ask questions and have had these answered satisfactorily. ☐
2. I understand that my participation is voluntary and that I am free to withdraw at any time, without giving any reason. If I withdraw within 6 weeks of commencement of the study my data will be removed. If I am involved in focus groups and then withdraw my data will remain part of the study. ☐
3. If I am participating in the focus group I understand that any information disclosed within the focus group remains confidential to the group, and I will not discuss the focus group with or in front of anyone who was not involved unless I have the relevant person's express permission. ☐
4. I understand that any information given by me may be used in future reports, academic articles, publications or presentations by the researcher/s, but my personal information will not be included and I will not be identifiable. ☐
5. I understand that my name/my organisation's name will not appear in any reports, articles or presentation without my consent ☐
6. I understand that any interviews or focus groups will be audio-recorded and transcribed and that data will be protected on encrypted devices and kept secure. ☐
7. I understand that data will be kept according to University guidelines for a minimum of 10 years after the end of the study. ☐
8. I agree to take part in the above study. ☐

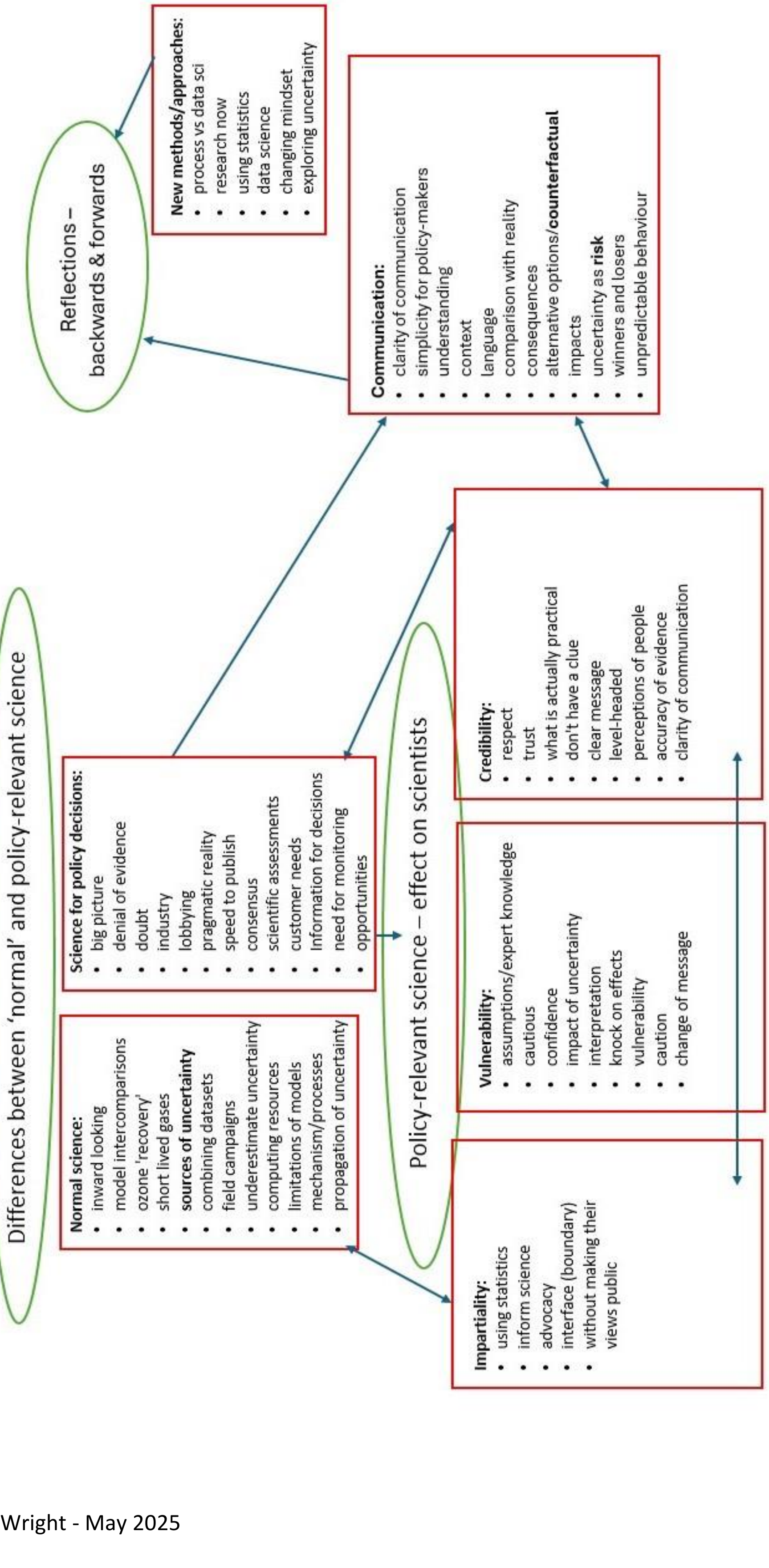
Name of participant:	Date:	Signature:

I confirm that the participant was given an opportunity to ask questions about the study, and all the questions asked by the participant have been answered correctly and to the best of my ability. I confirm that the individual has not been coerced into giving consent, and the consent has been given freely and voluntarily.

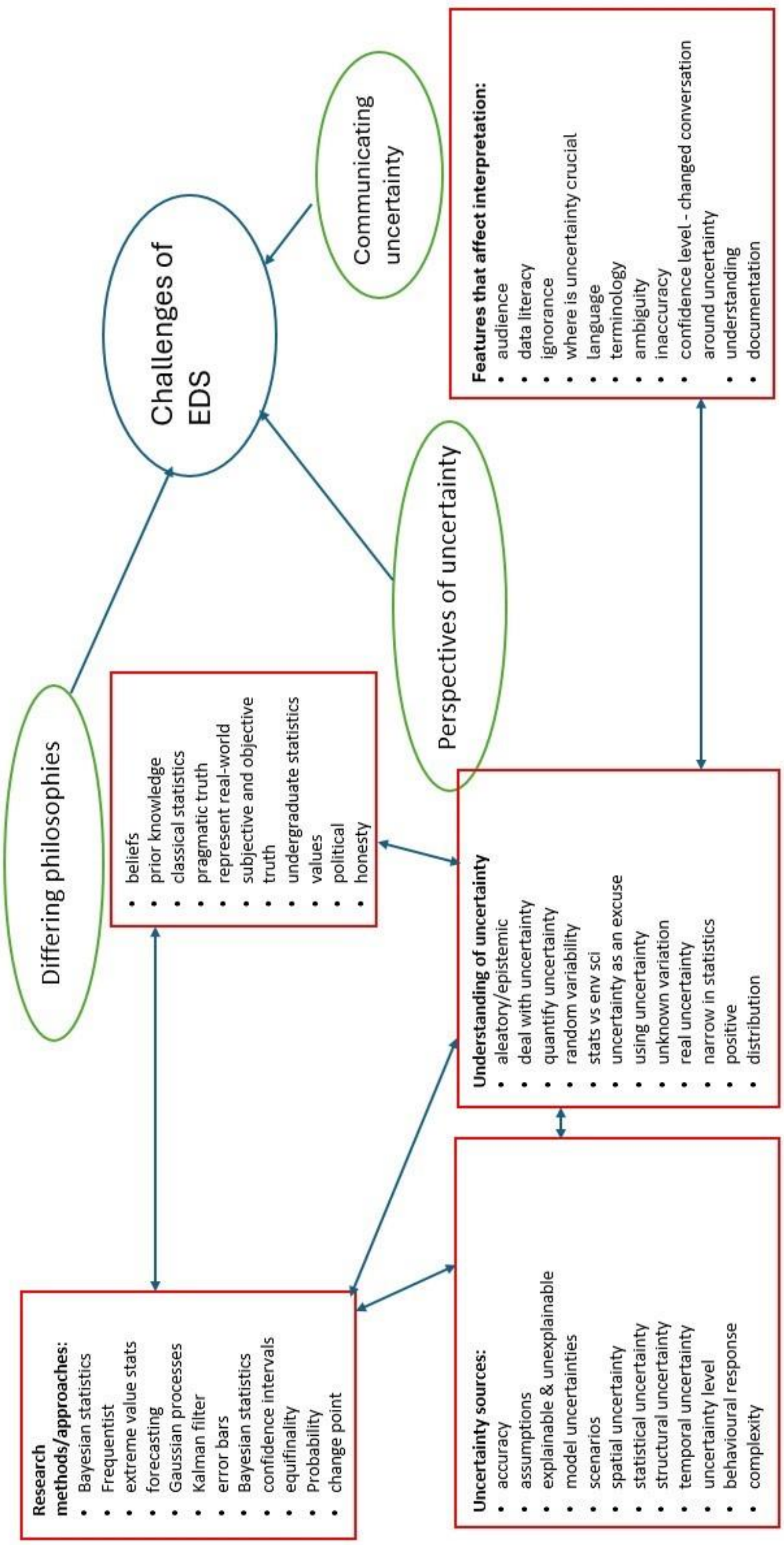
Signature of Researcher taking the consent __________ Date: DD/MM/YYYY

(One copy of this form given to the participant and the original kept by researcher at LU)

Appendix I. Codes and Themes from ozone interviews (chapter 5)



Appendix J. Codes and Themes from DSNE interviews (chapter 6)



Appendix K. Codes and Themes from CEEDS interviews (chapter 7)