International Journal of Disaster Risk Reduction 33 (2019) 449–476

Contents lists available at ScienceDirect

International Journal of Disaster Risk Reduction

journal homepage: www.elsevier.com/locate/ijdrr

Communicating model uncertainty for natural hazards: A qualitative systematic thematic review

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A R T I C L E I N F O

Keywords:
Communication
Uncertainty
Models
Decision-making
Engagement
Typology

A B S T R A C T

Natural hazard models are vital for all phases of risk assessment and disaster management. However, the high number of uncertainties inherent to these models is highly challenging for crisis communication. The non-communication of these is problematic as interdependencies between them, especially for multi-model approaches and cascading hazards, can result in much larger deep uncertainties. The recent upsurge in research into uncertainty communication makes it important to identify key lessons, areas for future development, and areas for future research. We present a systematic thematic literature review to identify methods for effective communication of model uncertainty. Themes identified include a) the need for clear uncertainty typologies, b) the need for effective engagement with users to identify which uncertainties to focus on, c) managing ensembles, confidence, bias, consensus and dissensus, d) methods for communicating specific uncertainties (e.g., maps, graphs, and time), and e) the lack of evaluation of many approaches currently in use. Finally, we identify lessons and areas for future investigation, and propose a framework to manage the communication of model related uncertainty with decision-makers, by integrating typology components that help identify and prioritise uncertainties. We conclude that scientists must first understand decision-maker needs, and then concentrate efforts on evaluating and communicating the decision-relevant uncertainties. Developing a shared uncertainty management scheme with users facilitates the management of different epistemological perspectives, accommodates the different values that underpin model assumptions and the judgements they prompt, and increases uncertainty tolerance. This is vital, as uncertainties will only increase as our model (and event) complexities increase.

1. Introduction

During recent natural hazard events such as the New Zealand 2010–2012 Canterbury earthquake and aftershock sequence, the communication of uncertain science advice, forecast, and model uncertainty, presented a challenging environment for planning and decision-making amongst key stakeholders, emergency managers and the public [1–6]. Globally this has been recognised as a fundamental issue [7]. Eiser and colleagues [7], summarizing the recommendations of the *Risk Interpretation and Action* working group of the International Research on Disaster Risk (IRDR) research programme, identified the need to understand how people interpret risks and how they respond based on these interpretations, particularly when making decisions under uncertainty. In this review, we focus on one particularly challenging issue: the effective communication to decision-makers of the uncertainties specifically associated with technical, model, and risk analysis. We focus on the communication pathway between technical science advisers (e.g. geologists, geophysicists, engineers, and social scientists) and responding agencies including emergency management (e.g., civil defence, fire service, police, army, policy makers, national and local government) and lifeline and support organisations (e.g., lifelines companies, transport, water, insurance and re-insurance). This communication pathway relates to operational planning, mitigation, response, and recovery needs. Thus, we refer to this group as ‘operational decision-makers’, while acknowledging that individual differences in their respective objectives, priorities, and interpretive and operational beliefs must be considered and accommodated in communication [2,8,9]. We recognise the consequent impossibility of

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https://doi.org/10.1016/j.ijdrr.2018.10.023
Received 28 May 2018; Received in revised form 24 October 2018; Accepted 26 October 2018
Available online 01 November 2018
2212-4209/

developing a one-size-fits-all approach to communicate to this range of decision makers [10], especially as tasks and needs change over the course of the response and recovery phases of large-scale disasters. However, we argue that providing a robust contingent communication framework that encapsulates key factors common across these users, provides an appropriate starting point for the development of effective strategies for science agencies and responding bodies (and the publics they are responsible for), allowing them to play complementary roles in communication processes.

Considering science advice in a natural hazards context, many levels of uncertainty exist. These range from the natural stochastic uncertainty (the variability of the system) to the epistemic uncertainty (lack of knowledge) [11,12], to scientists being uncertain about their knowledge and data, through to disagreement amongst scientists due to a) "incomplete information", b) "inadequate understanding", and c) "undifferentiated alternatives" [13], as well as issues arising due to conflicting scientific advice from scientific advisory bodies and individuals e.g., [14,15]. Developing strategies to manage uncertainty in crisis communication must go beyond the analysis of communication processes per se, and encompass contextual issues such as understanding the balance of information required at different times, and the psychosocial characteristics and processes that underpin communication during evolving events [1,3]. They must also encompass the evolving nature of negotiations between science providers and information receivers as they manage expectations regarding timelines, contents, and the concepts of probability and uncertainty [4] over time. Jolly and Cronin [4] state that "even if geophysical monitoring infrastructure and science capability is excellent and end-users are well engaged [and possess appropriate levels of knowledge and understanding], expectations of precision and accuracy of scientific advice are rarely met when attempting to understand uncertain natural systems" (p. 183). For example, engagement between scientific information providers and end-users may need to accommodate issues as diverse as planning to protect an international-profile public walking track in a volcanic park [6], through to communicating the distribution of hazard (maps) relating to ash fall, debris flows, ash advisories for aircraft, and warnings [5].

Another pressing issue when communicating hazard and impact models, relates to the fact that decision-makers are often presented with outputs (usually probability ranges) from proprietary systems and analysis platforms. These can act as a 'black box' where information regarding assumptions and analysis uncertainties is often not communicated to the decision-makers, limiting their decision-making capability. There is thus a need to identify effective ways to communicate these uncertainties to maximise the usefulness of these important analysis techniques, as well as a consideration of the ethics of whether or not to communicate those uncertainties and assumptions.

In the psychological literature, there is much discourse as to whether revealing the uncertainties associated with a risk assessment will strengthen or decrease trust in a risk assessor and their message [16,17]. Revelations of uncertainty has been identified as both enhancing the credibility and trustworthiness of the provider, and decreasing people's trust and credibility, with the outcome that emerges depending on several factors including the context, the relationship between provider and receiver, and past experiences [9,18]. Interpretations of, and the actions that ensue from, uncertainty can be affected by an individual's agenda and personal attitudes [16,18–23]. Thus, depending upon their role the risk to be managed by an individual or organisation can also encompass political, economic, and social implications of the hazard and management decisions, alongside the impacts of the hazard activity itself.

Give this complexity, it is not surprising that several international bodies (e.g., the International Panel for Climate Change, the World Meteorological Office, the National Research Council of the National Academies, and the International Commission on Earthquake Forecasting for Civil Protection), have generated guidelines to facilitate meeting this communication challenge [24–27]. However, these guidelines offer little detail or direction regarding the communication of the range of model uncertainties. It is unclear *how* to communicate this to decision-makers, whether it is *appropriate* to, and how that changes with the *context*. This has resulted in anecdotal discussions of model uncertainty being omitted from communications because of the ambiguity of 'how to communicate' this very technical uncertainty, and fear of overwhelming or confusing the receiver. Thus, in this review we address this issue by identifying key lessons from purposely sampled literature on the topic of communicating model uncertainty.

The issue of communicating uncertainty, communicating scientific uncertainty, and communicating model uncertainty has grown rapidly

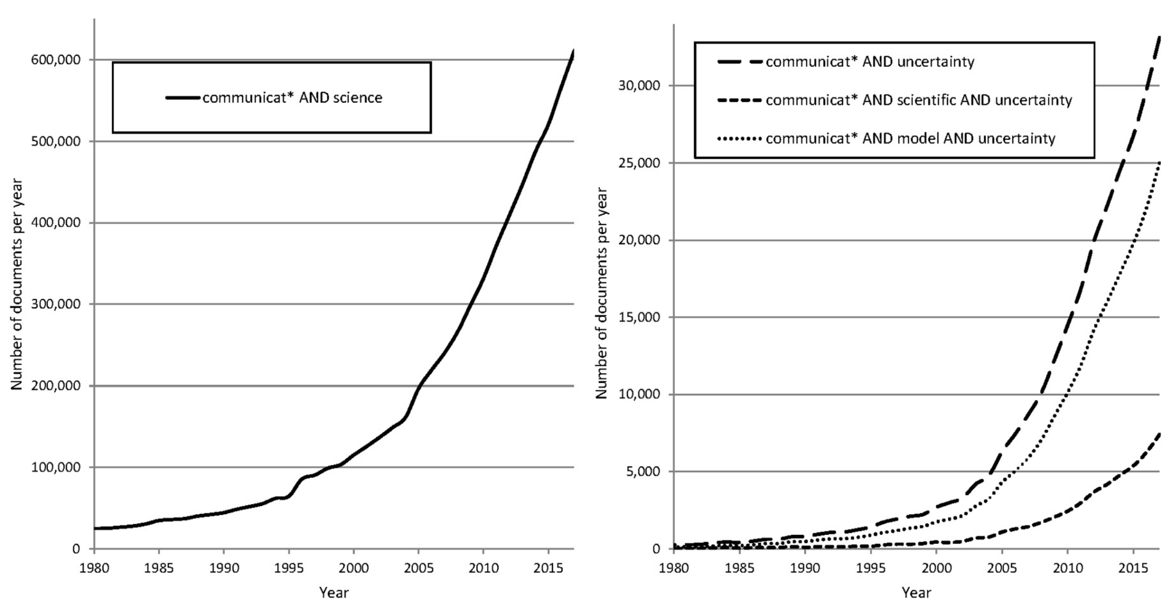

Fig. 1. An illustration of the increase in research into communicating science between 1980 and 2017, based on a SCOPUS search of all fields for the terms 'communicat* and science' (6,687,327 total documents), 'communicat* and uncertainty' (269,481), 'communicat* and scientific and uncertainty' (50,251), and 'communicat* and model and uncertainty' (191,093). All types of documents are included (journal articles, reviews, conference proceedings, books, book chapters, editorials and notes), and asterisks represent search 'wildcards'.

in the last two decades, as illustrated in Fig. 1. Thus, it is an opportune time to synthesise the key lessons from this literature to provide guidance for future communication, engagement, and to provide a robust platform for future research. To achieve this, we explore literature from across diverse disciplines and thematic contexts, ranging from weather and climate change to health, risk and policy, to help inform geohazard and risk communication practice. The common denominator is that these disciplines describe sources of hazardous events that are unfamiliar, present numerous and diverse sources of uncertainty that evolve over time within a given event, and, given the range of contingent influences on their sources, limit opportunities to predict what future events will look like. These factors combine in ways that mean that research into these phenomena is itself evolving. This broad search approach goes some way to encapsulating the diverse disciplines and stakeholders (from scientists and engineers, to policy makers, emergency response personnel, army, lifeline utilities, health boards, national and local government, and civil defence), decision contexts and decision-making demands, time-scales, and pressures that comprise "natural hazard emergency management". Decision-making and communication within disasters can also occur at many levels including agency-agency, team-team, within teams, individual-individual, and even individual-agency. Communications within one phase can also affect those in another (readiness communications can affect both the format of response communications, and the relationships with, and trust in, science advisors). Through this manuscript, our goal is thus to identify lessons for communicating model uncertainty by holistically drawing from lessons across a range of complex situations and disciplines. This, in turn, can provide a framework that can be tailored or adapted for more specific decision-making situations within natural hazard risk assessment and emergency management, and to provide a springboard for future communication protocols and systematic research into information and decision management in complex crisis events.

In this review, we initially consider *model uncertainty* to include all those uncertainties associated with modelling, such as: initial condition, parameter, boundary condition, governing equation, system representation, data validation, assumptions, and outcome uncertainty; and review that definition in Section 3.1. We next discuss our methodology (Section 2), summarise the characteristics of the literature found (Section 3), and present its key themes including the use of typologies, engagement processes, the influence of epistemic divides, ethics, trust, model confidence and consensus or dissensus, effective ensemble communication and spatial visualisation, and the importance of evaluation (Section 4). Finally, we identify key lessons from these themes for the identification, communication, and management of model related uncertainty, including areas that need future investigation (Section 5), outline our limitations and areas for future research (Section 6), and conclude with a new proposed framework for this process (Section 7).

2. Method

A systematic literature review process clearly documents the search terms, databases and dates of a search, as a well as the inclusion and exclusion criteria and the process of selection of the final documents for review [28–34]. The goal is to cover the range of perspectives on a topic, reduce the amount of bias that may occur in a traditional narrative review [35–37], and facilitate the replicability of the review process. However, we note that it is impossible to remove researcher bias when interpreting and synthesising findings. Unlike a traditional systematic literature review we employ an approach similar to a meta-synthesis [37–40] or qualitative thematic review [41], whereby the systematically identified literature is analysed thematically to find meaning and relationships. Thus, we do not present here an exhaustive review that captures, describes, or critiques the complete body of relevant literature. Rather, this report identifies and reviews the dominant themes or constructs that lie across a range of studies [41], employing a selective sampling procedure with inclusion, exclusion and relevance criteria, driven by core questions. While this means that we may miss texts relevant to identified themes, the review aims to identify the key lessons and issues for each theme which can then provide a robust framework for future systematic research.

We follow a 9 step process, outlined in Table 1. To identify the suitable search terms for our database search, we conducted a two-stage peer and expert consultation. Initially, informal conversations were conducted with active response and advisory scientists and communicators at a natural hazard science provider agency in Aotearoa NZ, to identify a series of core questions, which were refined based on the lead author's experience in both natural hazards communication and numerical modelling. The final questions are listed in Table 2. From these a series of search terms and synonyms were identified, as well as inclusion and exclusion terms. These were discussed with a further 5 expert colleagues to check for synonym appropriateness and duplicate meanings. The chosen terms are shown in Tables 3 and 4. We note that the questions and search terms relate primarily to communication influences, and not to decision influences. For example, the role of the precautionary principle on communication is not considered as it relates more to the decisions made for, or from, communicated products [18], and not on communication efficacy. Thus, it is beyond the scope of this review. However, future research could explore how the precautionary principle influences what uncertainties a scientist chooses to communicate (see also Sections 4.2.1 and 6).

Originally, a wide range of article databases were considered. However, the extremely high number of documents found required both a refinement of the search terms and the databases considered. Initially a Web of Knowledge search by topic between 1970 and 2015, using the terms listed in Table 3 returned over 1.5 million documents. The terms *Present** and *exposure** were removed due to their capturing irrelevant documents, and *Comm** was replaced with *communic**. This still produced an unmanageable 181,315 documents. A continued refinement of the *communication* subgroup of synonyms to *Communic* OR disclos* OR convey* OR acknowl* OR represent* OR summaris* OR summariz* OR disseminat**, and removing the term *crisis*, *conflict*, and *disaster*, still returned 90,950 documents. Thus, the search was instead conducted in SCOPUS, due to its ability to execute a more focused search on titles, abstracts, and key words. An initial search utilising the

Table 1
The 9 step systematic literature review process followed.

1) Determine key issues and questions with practicing scientists and communicators;
2) Identify key search terms, synonyms, and inclusion and exclusion criteria from those questions;
3) Peer review expert colleague feedback on those search terms;
4) Initial search of the databases with those terms;
5) Refinement of search terms as appropriate depending on documents found;
6) Final dated search;
7) Reading of abstracts to identify final suitable documents via inclusion and exclusion criteria;
8) Full reading of chosen documents and thematic coding of text in NVIVO (QSR International [42]) identifying key issues and findings;
9) Final thematic analysis of documents.

Table 2
the key driving questions used to help select search terms.

Types of models, model specific issues
- How does the type of model affect the communication of uncertainty? *(hazard, physical, risk, probabilistic, multi, hybrid, ensemble, insurance, etc.)*

Adopting a taxonomy or typology approach
- How is the uncertainty classified? *(e.g. assessment and use of taxonomy or typology)*

The role of time
- What approaches are used for different timescales? *(short, medium, long, time dependent)*

The role of audiences
- What approaches are used for different audiences? *(e.g. public, stakeholders, decision-makers, engineers, other scientists)*

Spatial issues
- What recommendations exist for communicating spatial, or geospatial, uncertainty?

Transfer and propagation of uncertainty, transparency and communication / Ensemble, multi- and multiple models, hybrid models
- What approaches exist for communication of uncertainty between models? *(e.g. nested, cascading, dependent uncertainties, multi- and ensemble models)*

Communicating model performance, trust in a model, choice to use a model, and model selection
- How do we effectively communicate model performance? *(to encourage understanding of expected performance in low data situations, to prevent model 'abandonment' by decision-makers based on one event)*

Communicating expert knowledge
- What approaches are used to communicate the role of the expert in uncertainty assessments? *(non-consensus, conflict, weighting, elicitation, subjectivity, expert judgment)*

Making communication "effective"
- What empirical evidence exists for the *effectiveness* of these various approaches? How is effectiveness measured and maintained?

Ethics, transparency, trust and motivators
- Are there any studies that consider the role of ethics, responsibility, trust and transparency in their decision to communicate uncertainty, or not; and how they communicate it?

Table 3
Search terms and synonyms as identified from the core governing questions in Table 2, and via feedback from natural hazard and communication colleagues. The asterisks in the above words act as 'wildcards' for the search engine. For example, "communicate*" instructs the search engine to look for any words that start with "communicat*", e.g., communicating, communicate, communicates, communications, communicated.

Key word group	Potential synonyms
Uncertainty	Uncertain*, ambigu*, conflict*, assumption*, limitation*, epistemic, aleator*, subjectiv*
Communication	Comm*, display*, disclos*, convey*, acknowl*, represent*, summaris*, summariz*, disseminat*, impart*, inform*, transmit*, present*, *visualis*, *visualiz*, share*, sharing, engage*, messag*, inquir*, discourse*, semiotic*, conversation, symbol*, language, media, discuss*
Model	Model*, simulat*, calculat*, estimat*, comput*, forecast*, project*, predict*
Hazard	Hazard*, disaster*, risk, crisis, climate*, medic*, weather, exposure, *fire*, earthquake*, seism*, cyclone*, typhoon*, hurricane*, inundat*, volcan*, tsunami*, *storm*, precipitat*, rain, wind, *flood*, tornado*, climate, pandemic, sea level

Table 4
Inclusion and exclusion search terms, based upon the questions raised in Table 2. Asterisks are wildcards, as explained for Table 3. In the above GIS refers to geographical information systems.

Key word group	Include if abstract contains this synonym
Assessment of uncertainty	Integrat*, quant*, qual*, inter-model*,weight*, assess*, identif*, probabil*
Evaluation	Evaluat*, assess*, effective*, implement*
Type of model	Hazard, physical, risk, probabilistic *(BBN, BET?)*, multi-model*, ensemble*, hybrid*, OEF, predict*, forecast
Classification	Classif*, taxonom*, typolog*
Time	Time*, term, short, medium, long, onset
Audience	Audience*, receiver*, stakeholder*, *user*, public*, decision*, scientist*
Spatial	Spatial*, geospatial, map*, GIS, *visualis*, *visualiz*
Education	Educat*, teach*, outreach, learn*, skill*
Model performance	Low resolution, data gaps, performance, quality, model choice
Expert	Expert*, elicit*, *consensus, judgment, judgement
Guidelines	Guideline*, protocol*, guidance
Ethics	Ethic*, Trust, transparen*, value*, responsib*, reveal*

Table 5
Final search term string used to identify documents for consideration in this review. A Scopus search on 10th August 2015 at 1:40 p.m. found 1131 of all documents or which 807 were Articles or reviews. Asterisks are wildcards, as explained for Table 3.

- TITLE (uncertain* OR assumption* OR limitation*)
- AND TITLE-ABS-KEY (communicat* OR convey* OR represent* OR *visualis* OR *visualiz*)
- AND TITLE-ABS-KEY (model* OR simulat* OR comput* OR forecast* OR predict*)
- AND TITLE-ABS-KEY (hazard* OR fire* OR earthquake* OR aftershock* OR hurricane* OR volcan* OR tsunami* OR storm* OR flood* OR tornado* OR risk OR climate* OR medic* OR weather OR science OR scientific)
- AND TITLE (communicat* OR convey* OR represent* OR *visualis* OR *visualiz*) OR (model* OR simulat* OR comput* OR forecast* OR predict*)
- AND LANGUAGE (english)
- AND NOT TITLE-ABS-KEY (food OR finance OR financial OR gun OR injury OR oil)

Table 6
The final number of considered documents, as found through each step of our search.

Source	Initial search criteria results	Results after refined search terms	Abstracts reviewed(after removing duplicates)	Chosen for full read	Final chosen
Web of Knowledge	> 1.5 Million	90,950	–	–	
Scopus	68,004	1131	1131	85 *(Score: Article > = 3; Others > = 4)*	79
PsychInfo	18	–	6	3	3
Mendeley database	37	–	23	14 + 7	13
Expert recommendations	–	–	54	18	13
Forward backward search					3
Total documents included				**127**	**111**

terms above, returned 68,004 English language documents. Excluding the terms *food*, *finance, financial, gun, injury,* and *oil*, reduced the number to 25,306. The search was further refined so that the *uncertainty* synonym groups and either the *model* or *communication* synonym groups must appear in the title of the article. This resulted in the final search term string shown in Table 5, which on 10th August 2015 produced 1131 documents, of which 807 were Articles or Reviews.

Unfortunately, an initial automatic text based search on these documents' abstracts using the exclusion and inclusion search terms shown in Table 4 excluded relevant documents and included those deemed not useful. Thus, the 1131 abstracts were each individually read by the lead author and given a relevance score of 1–5, using the questions in Table 2 as inclusion criteria, and the degree to which it specifically discussed *communicating* model uncertainty rather than the technical computational details of uncertainty. A high number of the documents considered the propagation of uncertainty between models (a core question, Table 2). However, these focused on the technical and procedural mathematical and computing process of that propagation, with little focus on the communication. Thus, we excluded this item from our search criteria, and suggest it should be the focus of future research.

After reading and scoring the document abstracts, those classified as Articles or Reviews by SCOPUS were chosen if their score was 3 or more, and those classified as 'Other' documents (chapters, conference papers, editorials, etc.) were chosen if their score was 4 or more. After this process, the number of documents was reduced from 1131 to 85. To ensure that relevant cognitive studies were not excluded, the search process included the PsychInfo database. This search was restricted to titles and abstracts, producing 3 more articles (see Table 6). In addition, the lead author's Mendeley [43] database of documents on communication, science advice, decision making, and natural hazards, built over the previous 7 years was searched via a title search on the terms "(uncertain* OR assumption* OR limitation*) AND ((communicat* OR convey* OR represent* OR *visualis* OR *visualiz*) OR (model* OR simulat* OR comput* OR forecast* or predict*))", producing an additional 21 relevant documents. Finally, a further 18 were identified during the conduct of the project and from expert colleague recommendations. A final 127 documents were thus identified for full text review, as shown in Table 6. From these, 19 were rejected due to relevance issues or being too computationally focused. A further 3 were added via a citation forward and backward search, leading to a final 111 for the thematic analysis stage.

Table 7
The number of documents found per year.

Year	Number of documents	Year	Number of documents
2015	15	2007	11
2014	11	2006	1
2013	10	2005	5
2012	9	2003	2
2011	13	2002	3
2010	8	2000	1
2009	9	1997	2
2008	10	1996	1

Rather than use the specific questions identified in Table 2 to interrogate the 111 documents, or identify pre-existing categories for content or coding analysis of the chosen documents as of a classic systematic literature review [31,44], we adopt an approach similar to that of Johnson et al. [34]. During reading of each manuscript, sections of text deemed relevant were assigned to codes. All identified codes were then collated into key themes, and iteratively refined, and reviewed to represent the main findings and issues of the literature. This is similar to a thematic qualitative analysis to identify patterns of meaning [45], and can also be described as a meta-synthesis [37] or qualitative systematic thematic review [41]. The goal is not to reduce findings (as of a meta-analysis or standard systematic review) but rather to analyse and synthesise the key elements of each document, 'with the aim of transforming individual findings into new conceptualizations and interpretations' (Polit and Beck, as cited in Cronin et al. [37], p. 1157) that can support developing future research questions. In total 24 themes and subthemes were identified from our documents, discussed next.

3. Summary of paper characteristics

Fifty-eight % of the 111 eligible documents have publications dates of 2011–2015 (see Table 7), demonstrating the increasing interest in model uncertainty communication, as well as the increase in general journal publications in recent years. Journal disciplines are dominated by Risk Analysis and Assessment, Geosciences and Geography, Environmental Management, Meteorology, Visualisation, Climate Change and Health (Table 8), but also include a wider scope from psychology, policy, communication, business, and environmental law. Based on the citation counts reported by SCOPUS [46] at the time of our initial search (10th August 2015), we can identify documents that have been particularly influential in the literature (Table 9), including Shackley and Wynne [47] (200 citations), Pang et al. [48] (159 citations), and Leyk et al. [49] (114 citations).

Using Scopus' classification, 74% are articles or articles in press, 14% conference papers and the rest are book chapters, guidance notes, review papers, and editorials (Table 10). During the full thematic reading of the documents, these were re-categorised by actual document content demonstrating that the majority are review or opinion papers (67%) or contained a large review section within. These were followed by empirical and case studies (48%), methodologies and frameworks (26%), evaluations (11%), and guidelines or critiques of guidelines (9%). Note these are not mutually exclusive categories (Table 10). The disciplinary focus was dominated by climate change (23%), flood forecasting (13%), weather forecasting (9%), clinical practice (7%), and natural hazards and emergency management (6%). Other topics ranged from ecology to journalism and law (Table 11). Before discussing the themes of these documents, we first clarify our definition of model uncertainty used from hereon.

Table 8
The number of documents for each classified journal discipline.

Journal discipline	Number of documents	Journal discipline	Number of documents
Risk Analysis and Assessment	10	Mechanics and Engineering	4
Geosciences, Geography	11	Psychology	4
Environmental Management	9	Water Science	3
Meteorology	9	Policy	3
Visualisation	9	Computing	2
Climate Change	9	Sustainable Development	1
Health	7	Oceanography	1
General Science	6	Mathematics and Physics	1
Ecology	5	Communication	1
Hydrology	5	Environmental Law	1
Cartography and GIS	4	Business	1
Ethics and Philosophy	4	Sociology	1

Table 9
The citation counts from Scopus at the time of our search.

Number of Citations	Number of documents	Documents
Unassigned	49	
1–5	21	
6–10	12	
11–15	4	[50–53]
16–20	6	[54–59]
21–30	7	[60–66]
31–40	3	[67–69]
41–50	3	[70–72]
51–100	3	Spiegelhalter et al. [73]; Oppenheimer et al. [74]; Schmidt-Thome and Kaulbarsz [75]
114	1	Leyk et al. [49]
159	1	Pang et al. [48]
200	1	Shackley and Wynne [47]

Table 11
The main hazard and disciplinary focus or thematic context of the documents.

Main Hazard / Discipline focus	Number of documents
climate change communication, ocean acidification	25
flood, flood forecasting, flood risk management, hydrological, hydrometeorological	14
wind, weather, rain, temperature forecasts	10
clinical practice, healthcare, pharmacology	8
natural hazards, emergency management	7
engineering, engineering modelling	3
ecology	3
water management	2
Risk assessment, impact assessment, governance	2
journalism	1
law	1
experimental economics	1
Other / general science communication	34

Table 10
The type of documents found.

SCOPUS Classified Publication type	Number of documents	Identified Document Content	Number of documents
Article	79	Review	56
Conference Paper	15	Empirical study	33
Book Chapter	6	Case study, examples	20
Guidance Note	4	Opinion	18
Review	3	Methodology	16
Article in Press	3	Framework	13
Editorial	1	Evaluation	12
Workshop Proceedings	0	Guidelines and critiques	10

3.1. A note on the definition of model and structural uncertainty

Several reviewed documents present specific typologies and classifications of uncertainty, discussed further in Section 4.1. In these, *'model uncertainty'* describes the broad range of uncertainties associated with the full modelling process, including: model structure uncertainty, model technical uncertainty, initial condition uncertainty, external driving force uncertainty, forcing data, parameter value uncertainty, scenario uncertainty, data uncertainty (e.g. for calibration, validation, or boundary conditions), and model outcome uncertainty [11,24,58,63,68,72,74,76–85]. Defining two of these sub-categories in particular, the *model structure uncertainty* refers specifically to the uncertainty in how the model describes the system, and the choice of governing equations and interrelationships [see 83]. The category *model technical uncertainty* then refers specifically to the uncertainty due to the decisions made in the development of the software, computer code, or hardware. Thus some of our core questions (Table 2) relate to the specific model *structure* uncertainty and the uncertainty in the model description itself, while others relate to the broader range of uncertainties described above and associated with the modelling process.

Thus we update our initial definition to use the term '*model related uncertainty'* (or '*model uncertainty'*) to encompass the full range and categories of uncertainties associated with the entire modelling process, from defining the key problems, the structural equations and governing relationships, through to the computational and validation issues, the verification and calibration via source data, and the uncertainties related to initial conditions, parameters, variables, as well as the final outcome uncertainty. It is this broader communication of model uncertainty that we aim to improve via this review. We then use the term *'structural uncertainty'* to specifically refer to the sub-set of that model uncertainty that is associated with the representation of a physical or social system by a model, the uncertainty in the descriptions, governing equations and interrelationships. We note that to date this very specific uncertainty has often been under-reported (see [63,74]) and can include simplifications and scientific judgements [63], which can have particular importance when considering multi-model and ensemble model assessments [58]. We note that uncertainty related to the 'unmodelled' components, which are those aspects not (yet) incorporated into models (due to lack of information, understanding, modelling capability, model resources, etc.), could be included either specifically in 'structural uncertainty' if it pertains to the core model representation, or more generally in 'model related uncertainty', particularly if it pertains to input parameters, variables, and initial conditions.

4. Key themes in the literature

Key thematic areas identified in the 111 documents are summarised in Table 12, and include the need for structured typologies, taxonomies or classification schemes to effectively identify and communicate the full range of uncertainties (discussed in Section 4.1), and their role in

Table 12
The themes and sub-themes found through our meta-synthesis review of the 111 chosen documents. Sub-themes were identified by the dominant topics coded through a reading of each manuscript (as described in Section 2), and were then grouped into the main themes indicated in bold. Sub-themes were not mutually exclusive, thus there are some documents that were coded for multiple sub-themes. However, to remove excessive duplication across related sub-themes, coded manuscripts were assigned to a sub-theme only when they contained a considerable discussion or exploration of the topic, and not for brief overviews.

Theme	#	Document Reference
Typologies, categories, and classification schemes for communicating uncertainty		
General typologies, taxonomies, and categorisations	35	[25,55,56,58,63,64,67,68,71,72,77–81,83–102]
Typologies specifically for uncertainty in spatial visualisation	13	[10,48,49,70,72,77,103–109]
Structural uncertainty definitions	17	[11,24,58,63,68,72,74,76–85]
Engagement processes, and the complexities that influence effective engagement		
Engagement and participatory approaches	10	[11,67,69,75,89,93,99,110–112]
Trust	5	[23,60,113–115]
Epistemic differences and divides, philosophy of science, post-normal science	12	[47,50,54,56,67,86,97,98,100,115–117]
Psychology, mental models, individual beliefs	7	[11,53,93,102,115,118,119]
Ethics	4	[82,85,120,121]
Methods and techniques for communicating specific uncertainties (e.g. graphs, probabilities), and complex uncertainties (e.g. confidence and consensus)		
Visualisation: maps, spatial, GIS, specific techniques	29	[10,25,48,62,72,77,91,103–107,109,111,116,118,122–133]
Novel techniques: sonification	3	[48,77,133]
Evaluation	8	[62,105,106,116,118,123,128,134]
Particular Examples of Empirical investigations	5	[125,127,129,131,134]
Visualisation: graphs, tables, images	9	[25,57,62,66,73,118,119,135,136]
Probabilistic statements and terms	18	[11,24,25,52,53,60,61,73,81,85,101,129,136–141]
Timeframes	12	[87,89,92,106,113,131,138–140,142–144]
Ensembles	15	[50,51,58,59,65,66,68,92,108,109,121,142,145–147]
Model confidence, confidence in evidence, bias	13	[24,25,50,56,79,85,88,94,101,121,140,141,148]
Consensus and dissensus	10	[64,74,79,81,82,98,114,140,141,148]
Articles that list a summary of recommendations and guidelines for communicating uncertainties		
Specific recommendations/guidelines	20	[11,53,56,64,72,81,84,85,88,93,94,101,127,131,132,137,139,140,144,149]
Specific operational guidelines	4	[24,25,76,150]
Critique of IPCC guidelines	11	[11,53,64,79,81,101,132,139–141,148]
General uncertainty communication	13	[23,59,68,98,101,113,114,135,143,144,149,151,152]
Other themes		
Propagating and cascading uncertainties	7	[65,70,78,88,96,144,147]
Decision making	26	[25,50,60,71,79,83,93,97,100,106,108,110,112,116,117,128,129,135–137,140,142,146,148,152]

Table 13
Papers that consider typologies and uncertainty classifications. Note for the first category, Janssen et al. [67], van der Sluijs et al. [86], and Ekström et al. [87] all build on the matrix of Walker et al. [83]; Kloprogge et al. [88] utilises a 'pedigree matrix', building on Funtowicz and Ravetz [153]; and Höllermann and Evers [89] utilises the uncertainty risk triangle of Stirling [98].

Approaches to classify uncertainty	Document references
Documents, reviews, or proposes Typologies, Taxonomies, systematic classification, or pedigree matrices	[55,67,78,83,86–89,98]
More generalised definitions and classifications of sources of uncertainty	[25,56,80,84,85,95,96]
Case studies considering classifications of uncertainty and assessing end user perspectives on uncertainty	[58,63,68,90,93,94,102]
Typologies developed and proposed specifically for spatial visualisation	[10,48,70,72,77,103–109]

Geographical Information Systems (GIS) and spatial visualisation of uncertainty in particular (Section 4.1.1). The need for effective engagement processes to assess both the decision needs for communication, and what uncertainties to prioritise, analyse, and communicate was raised repeatedly (Section 4.2), with a particular acknowledgement of the challenge of such a process when epistemic divides exist (Section 4.2.1), the role of an individual's worldview (Section 4.2.2), and the ethical and trust issues relating to communicating these uncertainties (Section 4.2.3 and Section 4.2.4). The third broad category relates to the communication of complex uncertainties, including model confidence and bias (Section 4.3.1), consensus (Section 4.3.2), multi-model and ensemble related uncertainties (Section 4.3.3), and effective visualisation of spatial uncertainty (Section 4.3.4). Additional themes relate to specific methods, techniques and challenges of communicating these technical and model related uncertainties, including effective visualisation of graphs, tables and images, communicating probabilities, and communicating timeframes (Appendix A). Finally, the lack of evaluation of what are considered best practice techniques, and suggested criteria for evaluation emerged as a theme (Section 4.4). Thirteen documents (12%, Table 12), discussed the more general issues of communicating uncertainty, alongside their more detailed discussions of model uncertainty, discussed further in Section 5. Finally, 35 documents discuss specific recommendations, operational guidelines for communicating modelling uncertainties, and critiques of those approaches (Table 12, discussed in Section 5).

4.1. *Typologies, taxonomies, categories, and classification schemes*

A key theme identified was the need for specific categories, typologies or taxonomies for uncertainty, to help identify, assess and communicate them, with 35 (32%) of the documents reviewed explicitly advocating for this (see Tables 12 and 13). A number of documents suggested such typology schemes can facilitate communication by bridging epistemological cultural differences between disciplines [56,78,86,97,100] discussed further in Section 4.2.1. However, creating a unified classification scheme can, because of these epistemological differences, be challenging [77]. Thus, there is a need to identify or develop a suitable scheme for the communication issue in hand, which adopts an engagement or elicitation approach [e.g., 99] to develop a mutual understanding between scientists and decision-makers of the relevant uncertainties that need to be assessed and communicated to support their decision needs [71], discussed further in Section 4.2.

In advocating for the use of formalised typologies for uncertainty, Walker et al. [83] highlight that "understanding the various dimensions of uncertainty helps in identifying, articulating, and prioritising critical uncertainties, which is a crucial step to more adequate acknowledgment and treatment of uncertainty in decision support endeavours" (p. 5). As stated by Stirling [98], it is vital to identify all types of uncertainty in technical science advice such that science advice can become more rigorous, robust and 'democratically accountable' (p. 1029). Both Aven and Renn [101] and Adler and Hirsch Hadorn [79] also support distinctions of uncertainty associated with modelling to 'avoid misinterpretations of uncertainty characterizations' [79; p. 668] particularly in the case of structural model uncertainty, as well as to improve communications that accurately reflect 'extreme outcomes and a poor knowledge base' as appropriate [101; p.10].

Methods for identifying and classifying uncertainties become particularly important as many forecast, model, risk, and technical scientific communications tend to focus on the statistical output uncertainty, whether the model assumptions and relationships are reasonable, and the calibration data representative. This is, however, often incomplete. Deeper uncertainties can form, particular due to interdependencies, resulting in much larger (practical) uncertainties than the statistical uncertainty usually communicated. This circumstance requires prioritisation of their analysis and communication over that statistical uncertainty [83].

Several schemes analysed served to define and classify the uncertainties, listed in Table 13. A scheme often referred to is that of Walker et al. [83] who developed a typology for uncertainty management in model-based decision support, based upon a synthesis of existing taxonomies, frameworks and typologies of uncertainties from different decision support fields. This considers three overarching categories (p. 8): 1) the *location* of the uncertainty which considers: a) the context of the model, b) the model uncertainty, including both the model structure uncertainty (the uncertainty about the form of the model itself) and the model technical uncertainty (the uncertainty about the computer implementation), c) inputs such as the reference system and external forces and other input variables, d) parameter uncertainty, and e) model outcome uncertainty, which is the "accumulated uncertainty associated with the model outcomes of interest to the decision-maker" ([83], p. 9). Next, 2) The *level* of the uncertainty considers where the uncertainty sits along a scale from determinism, statistical uncertainty, scenario uncertainty, recognised ignorance, indeterminacy, through to total ignorance, where "we do not even know that we do not know" (p. 13). Finally, 3) the *nature* of the uncertainty considers whether the uncertainty is epistemic and due to knowledge imperfection, or whether it is a variability uncertainty which is of particular importance in human and natural systems that considers social, economic, and technological developments (p. 14). This variability (or ontological uncertainty) can thus be further divided into behavioural variability (micro), social variability (micro and macro) and natural randomness. Having defined these uncertainties, Walker et al. [83] then develop an uncertainty matrix that illustrates the location, level, and nature of the uncertainty associated with models and provides a systematic and graphic overview of the range of essential uncertainties (see Tables 14 and 15). Such a matrix only applies at one time during the decision support process, such as during a) the preparatory pre-analysis phase when the problem is being framed and the model built, b) the analysis phase acting as a checklist during model use, assessment of the results, reporting and communication, and c) during peer review or self-evaluation for quality control.

Walker et al.'s [83] uncertainty matrix represents the most utilised typology relating to the modelling process found in the selected literature. It was used and developed by van der Sluijs et al. [86], Ekström et al. [87], Kwakkel et al. [55], and Janssen et al. [67] (see Table 13). Janssen et al.'s [67] addition included scores distinguishing the "*qualification of knowledge base* (what are weak and strong parts in the assessment) and [the] *value-ladenness of choices* (what biases may shape the assessment)" (see van der Sluijs et al., [86], p. 266), for each location of uncertainty (see summary in Table 15), and employ this matrix within a guidance decision system for managing and communicating uncertainty for the Netherlands Environmental Assessment Agency (then RIVM/MNP). This is used within a checklist approach for problem framing and project design (see also [86]). Ekström et al. [87] adds the categories 'aim and genesis' and 'recognised weaknesses' to that of Walker et al. [83]. These categories capture the "specific aim(s) of the assessment, the circumstances under which the study was conducted, and any important caveats" [87; p.118]. They also include the stage of the assessment, including aspects such as 'main policy focus', 'spatial scale', and 'analytical approach'. Kwakkel et al. [55] updated the matrix of Walker et al. [83] based on its applied use and critiques, to consider four levels of uncertainty: 1) shallow uncertainty, 2) medium uncertainty; 3) deep uncertainty; and 4) recognised uncertainty; in an attempt to capture the differences in the types of scales used when assigning likelihood to things or events. They also include *ambiguity* as an additional category of the nature dimension, to account for the differences in frames between different stakeholders due to a plurality of perspectives and values. The updated system is summarised in Table 15.

Kloprogge et al. [88] adopt a different approach by developing a pedigree matrix for the assessment of the value-ladenness of assumptions made throughout a modelling process. Types of value-ladenness considered include practical aspects, epistemic, disciplinary-bound epistemic, and socio-political issues. The method uses a pedigree matrix [building on 153], which 'addresses the strengths and weaknesses in the knowledge base behind a number by critically reviewing the production process of the number and the scientific status and underpinning of the number' [88; p. 293]. Kloprogge's matrix has 7 criteria: 1) influence of situational awareness, 2) (im)plausibility, 3) choice space, 4) (dis) agreement among peers, 5) (dis)agreement among stakeholders, 6) sensitivity to view and interests of the analyst, and 7) influence on results; each of which are ranked from 'weak' to 'strong' via qualitative expert judgment.

The goal is to facilitate the identification, analysis, prioritisation

Table 14
An example of an uncertainty typology matrix, as of Walker et al. [83], outlining the various dimensions of uncertainty. As stated by Walker "in filling in the matrix, one should be aware that the level and nature of the uncertainty that occurs at any location can manifest itself in various forms simultaneously" (p.14).

Location		Level			Nature	
		Statistical Uncertainty	Scenario uncertainty	Recognised ignorance	Epistemic Uncertainty	Variability uncertainty
Context	Natural, technological, economic, social and political representation					
Model	Model structure					
	Technical Model					
Inputs	Driving forces					
	System data					
Parameter						
Model outcomes						

Table 15
Example typology matrices, illustrating alternative categories. Table a) lists the column categories used in these matrices representing the *Level* and *Nature* of uncertainty, and the qualification and value-ladenness as appropriate. Table b) lists the row categories representing the *Location*. Further examples can be found in Ekström et al. [87], Stirling [98], and Skeels et al. [77,78].

a) Column categories

Walker et al. [83]	**Level**			**Nature**							
	Statistical Uncertainty	Scenario uncertainty	Recognised ignorance	Epistemic Uncertainty	Variability uncertainty						
Kwakkel et al. [55]	**Level**				**Nature**						
	Level 1: Shallow uncertainty	Level 2: medium uncertainty	Level 3: deep uncertainty	Level 4:Recognised ignorance	Ambiguity	Epistemology		Ontology			
Janssen et al. [67]	**Level of uncertainty (from determinism, through probability and possibility, to ignorance)**			**Nature of uncertainty**		**Qualification of knowledge base**			**Value-ladenness of choice**		
	Statistical uncertainty	Scenario uncertainty	Recognition ignorance	Epistemic	Variability	-	0	+	-	0	+
Höllermann & Evers [89]	**Level: Fundamental**			**Level: Procedural**							
	Uncertainty	Ambiguity	(Recognised) Ignorance	Norms and regulations	Resources	Competence	Knowledge transfer		Risk perception	Strategic liability and responsibility	

b) Row categories

Walker et al. [83]		**Kwakkel et al.** [55]		**Janssen et al.** [67]		**Höllermann & Evers** [89]	
Context	Natural, technological, economic, social and political representation	System boundary		Context		Location: Fundamental	Boundary conditions
Model	Model structure	Conceptual model		Expert Judgment			Data
	Technical Model	Computer model	Model structure	ModelInputs	Structure		Model output
Inputs	Driving forces		Parameters inside the model		Implementation		Parameter
	System data		Input parameters to the model		Parameters		Expert Judgement
Parameter		Input data			Inputs	Location: Procedural	Political framework
Model outcomes		Model implementation		Data			Financial and human constraints
		Processed output data		Outputs			Peer-review
							Culture of communication
							Relevance
							Conflicting interests and ownership

and communication of the value-ladenness (bias) of assumptions in the full calculation chain that leads to a model assessment output. Unlike some of the other typologies discussed, the influence of each assumption on the final result is included in the assessment, allowing for overly influential biased assumptions to be addressed. Utilisation of such a tool addresses the issue that it is not possible to adequately communicate modelling related uncertainty if there is a lack of clarity as to what they are. Kloprogge et al. [88] do however emphasize that such an approach isn't appropriate for every day-to-day assessment due to the time-consuming nature of the process. They suggest it should be followed in selective situations where 'the policy relevance of the issue of assumptions is highest' (p. 300). Kloprogge et al. [88] provide criteria to help identify those cases.

Building across existing approaches, Höllermann and Evers [89] developed an alternative approach that considers a 2 × 2 matrix (see summary in Table 15). This approach considers on one axis the level and location of the uncertainty, and on the other the causes of the uncertainty including a) the fundamental uncertainties such as aleatoric or epistemic uncertainties, and b) the procedural uncertainties due to the planning process. They state that such a matrix can be used in a risk governance framework to assist communication and decisions at each step, including 1) pre-assessment and framing, 2) appraisal and risk estimation, 3) characterisation and evaluation, and 4) management; acting as a tool to assist knowledge transfer and communication. Their approach attempts to capture in one scheme both the various approaches used to reduce scientific uncertainty, and the approaches used in risk governance uncertainty acceptance.

Considering instead an approach that focuses more on the definitions of uncertainty to assist information visualisation, Skeels et al. [78] develop an alternative classification scheme that considers three levels: 1) the measurement precision; 2) the completeness – which includes missing values, sampling aggregation, and level of uncertainty awareness; and 3) the inferences – which includes the predictions, modelling, and describing of past events. Across all levels two additional categories are added; defining disagreement and credibility uncertainty. The level of uncertainty awareness considers a) known knowns; b) unknown knowns; and c) unidentified unknowns, which is the worst case of unknown. This type of classification scheme aims to create a tool to facilitate discussion and understanding of uncertainty with diverse users. They also identify issues with visualising uncertainty, depending on where the uncertainty sits within the classification scheme, discussed further in Section 4.1.1.

Other schemes that adopt more generalised definitions and classifications of uncertainty include those of Murphy et al. [56], Briggs et al. [84], Han [85] and Bjerga [80]. Several of the studies reviewed used typology and classification schemes in specific case studies and examples (see Table 13). These may provide useful exemplars for people developing classification schemes. These include approaches from health care, pharmacology and clinical settings [63,84,93,102], climate change [58,90,94], ecology [72,91], and flood forecasting [92]. It is beyond the scope of this review to describe each of those schemes in detail here, and we direct users to the documents for details. In addition to the texts identified in the systematic search, we direct readers to Thompson and Warmink's [154] framework for identifying and classifying uncertainties that adapts Walker et al., [83] typology such that the 'nature' dimension includes linguistic, knowledge, variability, and *decision*; the 'location' dimension includes context, input, model structure, model technical, parameters; and the 'level' dimension includes statistical, scenario, and recognised ignorance of uncertainty. Of particular use are the decision trees they provide that can facilitate identifying where an uncertainty sits within this uncertainty matrix.

Several documents, including Farhangmehr and Tumer's [95] complex design systems work, Blind and Refsgaard's [71] work on water resources management, Roy and Oberkampf's [96] discussion of flow simulations in engineering, Gill et al.'s [25] guidelines for meteorological forecasting and Parker's [68] global weather and climate models, do not adopt formalised typologies for analysis or communication. Rather they identify general categories and sources of uncertainties. While their definitions assist understanding of the range of uncertainties that may need to be accommodated, such approaches, without a fully structured typology, run the risk of the accidental omission or oversight of a critical uncertainty. In addition, the approach used in the field of applied systems analysis by Grubler et al. [97] includes the categories *linguistic* uncertainty to represent vagueness in problem formulation, and *contingency/agency* uncertainty which arises from human intentionality, whereby the very policy decision made in a particular study contributes to uncertainty itself. An alternative approach by Stirling [98] uses a broader classification matrix, which acts as a tool to assist in model assessment that encourages experts to consider ambiguity, uncertainty, and ignorance, as well as risk when analysing information that supports a decision, deciding how to communicate, and when making a decision. How definitions of uncertainty apply in socio-environmental systems including the uncertainty due to human choice and ontological uncertainty in terms of how the system relates to the nature of the world are also discussed by Cornell and Jackson [155], as well as by Patt and Dessai [11] who raise the issue of human reflexive uncertainty (which arises as simulated predictions influence human actions, which in turn impact the systems being predicted). Finally, of particular interest is the point raised by both Aven and Renn [101] and Han [85] that probability is often erroneously used to describe all uncertainty, when usually it does not include other epistemological, structural uncertainties and value judgements, nor alternative definitions of risk and different understandings of probability.

4.1.1. Typologies for uncertainty in spatial visualisation

When it comes to communicating uncertainty associated with maps, GIS, or other spatial visualisation tools, 13 documents (12%) further the schemes discussed above by considering the uncertainties associated with data classification, projection, and visualisation (Tables 12 and 13). Thomson et al. [70] propose a typology of geospatially referenced information based upon the spatial data transfer standards of the USGS for data quality [156], which incorporates accuracy/error, precision, completeness, consistency, lineage, currency/timing, credibility, subjectivity, and interrelatedness. They also include classification schemes identified in the fields of scientific visualisation and information visualisation [10,48] which matches the data type (scalar, multivariate, vector, and tensor) to the visualisation extent (discrete, continuous). In addition, they include imperfect knowledge, which incorporates incomplete information, inconsistency, complicated information, uncertainty, and imperfection due to corrupt data or information, as well as imperfect presentation.

With regard to digital elevation models (DEM) and visualisations of their uncertainty, Brus and Svobodova [106] consider spatial data uncertainties to include positional uncertainty, attribute uncertainty, time uncertainty, incompleteness, and logical inconsistence. They also include three types of errors in DEM creation, including blunders, systematic errors, and random errors. Similar schemes that include measurement precision and data errors in the sources of visualisation uncertainties were found in a number of documents [72,77,103–105,107–109]. Elith et al. [72] uses the term *linguistic* uncertainty differently to that described in Section 4.1 above, and instead use it to describe the literal uncertainty that arises due to the duplication and uncertainty of word meanings when digitizing qualitative data and maps. Leyk et al. [49] additionally consider three domains for potential sources of uncertainty in GIS, including production-oriented uncertainty, transformation-oriented, and application-oriented. Specific techniques for visualising uncertainty are recommended by some of the above documents [10,48,72,104–107], discussed further in Section 4.3.4.

4.1.2. The purpose and use of typologies

It is clear that there is a wide range of typologies, taxonomies, and classification and definition schemes for uncertainties in decision analysis, model decision support, simulations, forecasts, model development, and communication. While it would be impossible to develop one uniform scheme, the development and use of an appropriate scheme can help to facilitate communication by bridging epistemological cultural differences between disciplines [56,77,86,97,100; see also Section 4.2.1]. This approach can also prevent erroneous or accidental omission of uncertainties in an uncertainty analysis [78], or the incorrect prioritisation of communication of one uncertainty over another [83]. This is particularly important in an environment where experts might be pressured to simplify their advice by policy-makers [98]. Stirling [98] advocates that we should move away from a narrow focus on risk to broader and deeper understandings of incomplete knowledge. They present an 'uncertainty matrix' that classifies and identifies uncertainty assessments, and state that this matrix can be used as a tool to facilitate better discussion with policy-makers (one of our 'operational decision-makers', Section 1), by catalysing 'nuanced deliberations' (p. 1030) and encouraging experts to look beyond risk to consider 'ambiguity, uncertainty, and ignorance using quantitative and qualitative methods'. Considering climate change forecasts, Budescu et al. [81] emphasize the importance of "specifying the various sources of uncertainty underlying key events and the importance of outlining their nature and magnitude to the degree that is possible" (p. 306), in order to set realistic expectations about whether these uncertainties can be reduced in the future or not.

The use of classification schemes can also help risk assessors identify ways in which the "level of uncertainty can be changed so that it becomes more informative (i.e., shifts from qualitative to scenario or statistical)… [or] …so that the data with the largest uncertainty is introduced towards the end of the analyses" [87]. The reviewed literature highlights that by developing and utilising these classification and typology schemes, scientists and modellers can work with stakeholders and decision-makers to help communicate and visualise the uncertainties in a modelling or forecast system, and prioritise which uncertainties should be the focus for reduction, analysis, and communication. However, in order for this to be successfully accomplished, scientists, modellers and risk analysts must develop an effective engagement or elicitation process with stakeholders and decision-makers to identify those relevant uncertainties and decision needs [71,89,98,99]. They could utilise an existing typology, or develop a typology as part of the process such that the contingency and agency uncertainties [97] and other human activity and decision related errors and uncertainties [56,83] can be incorporated. This relates to Beven et al. [157], who reviews various approaches to elicit expert opinions about sources of epistemic uncertainty, identifying this as a critical step in their framework for good practice in modelling. They recommend these uncertainties are then used to inform a sensitivity analysis of risk management decisions to explore whether they are robust to the chosen assumptions. As highlighted by Höllermann and Evers [89] it is through classifications and typologies of uncertainties in models, risk analysis, and forecasts, that we can help facilitate knowledge transfer into the risk governance processes. We next discuss the range of potential engagement approaches found through our review, and the role and impact of different epistemological, disciplinary cultures, and mental models in this process.

4.2. Engagement processes to assess needs, and the complexities that influence engagement

Ten (9%) of the documents found in our meta-synthesis focussed on engagement and participatory type approaches to communicating uncertainty between scientists and decision-makers (Table 12). Patt [110] points out that a particularly challenging issue is the wide range of uncertainty decision making models that exist to describe the stakeholders' thought processes, and addressing communications to meet those processes. These models can range from economic models (where framing of the communication is key), through to psychological models (where satisficing, heuristics, and bias play an important role), or political models (which depend on distinct worldviews, discourse, and where people interpret information in a way consistent with their own view). Rather than focusing on which model best describes the stakeholder's decision making process, and formatting communications to meet that process accordingly, Patt [110] suggest instead that the solution lies in adopting a participatory approach which can help make scientific information more credible and legitimate [see also 11]. This is rooted in a process of dialogue with attention to "two-way communication and the relationship between scientists and policy-makers" ([110, p. 231]).

This approach is particularly advantageous when considering the many dimensions of uncertainty, which can be difficult to communicate quickly in a traditional one-way communication process. An effective two-way dialogue allows scientists to communicate just enough information for decision-makers to judge whether they need more, rather than overwhelming them with all the information. An interactive dialogue allows the most important details to be made salient. In addition, a dialogue can help combat any loss of credibility that can arise in situations of highly uncertainty information. Patt states that the most important consideration when communicating to policy-makers (one of our 'operational decision-makers', Section 1) is to give 'decision-makers enough information to know when they need to invest the time and resources to take part in a participatory process, and when they do not' [110; p. 246]. Considering risk visualisations, Loucks [135] also highlight that what to communicate (in terms of level of detail and quantification) depends on audience needs, where communicators must listen and learn from their stakeholders in order to craft effective risk messages and communications that better reflect "the perspectives, technical knowledge, and concerns of the audience" (p. 50) [see also 10].

Faulkner [69], Janssen [67], and Beven [111] all promote participatory approaches that enable the users and decision-makers to identify alongside scientists their specific uncertainty information needs, to facilitate more effective management and communication of uncertainty. Faulkner et al. [69] consider the development of an uncertainty classification scheme in flood risk management, and indicate that a key problem with communication to date has been a lack of *ownership* of uncertainty, where communication to stakeholders has been one way and has not included purposive translations of the information (particularly between different domains of scientific complexity and operational needs), or shared ownership of the uncertainty. Their solution is to adopt a 'translational discourse', which is defined as "a conversation that maximizes the facilitation of the decision-making process" (p. 698), leading to a joint decision about which uncertainties should be modelled. For this to work, they state that a code of practice and professional guidelines are needed for the uncertainty estimation and translation discourse, which considers funding, leadership, and ethical standards. Such an approach also provides an audit trail to ensure no uncertainty is forgotten [111]. Janssen et al. [67] present a guidance system primarily for the identification and management of environmental assessment uncertainty which involves the development of a typology or taxonomy of appropriate uncertainties considered relevant by *both* the scientists and the stakeholders. They highlight that such a system, which focuses on the problem context and socio-political embedding, accountability, transparency, reflexivity, participation and extended peer review, provides a flexible structure to uncertainty management, which stimulates reflection and deliberation on "how uncertainties are (to be) handled and communicated effectively" [67; p.130]. Such an approach builds towards the "new social practice of science in a postmodern era" (p. 131) such as post-normal science and mode 2 science paradigms [158–161]. Mode 2 science advances on the traditional paradigm of scientific discovery (mode 1) and considers "socially distributed, application-oriented, trans-disciplinary" approaches to science that are subject to multiple accountabilities (see review in [162]), discussed further in Sections 4.2.1 and 4.2.2.

Developing uncertainty management and communication processes in a partnership model between scientists and users is also advocated for by Fischhoff and Davis [99]. They argue that effective communication depends on the decision needs of the stakeholders, identifying three typical decisions (action thresholds, fixed options, and potential options) and methods to characterise, analyse and communicate uncertainty for each of these effectively, via an engagement/elicitation scheme which incorporates a classification typology. They caution however, that communicating uncertainty can both simplify and complicate discourse, stating that uncertainty should be non-persuasive and honest (discussed further in Section 4.2.3).

Specific case studies adopting similar engagement and participatory approaches to developing and utilising typologies for knowledge transfer, communication and management of uncertainty can be found in Hirschberg et al. [112] for hydrometeorological forecast uncertainty, Höllermann and Evers [89] for flood risk management, Schmidt-Thome and Kaulbarsz [75] for climate change and GIS maps, and Politi and Street [93] who focus on a collaborative decision making approach to communicating and managing uncertainty between doctors and patients. The participatory development of typologies, which acknowledge and communicate uncertainty in a transparent shared manner with stakeholders, also helps to build trust in both scientists and in science information.

Found subsequent to our initial search, Cornell and Jackson [155] outline the importance of different engagement and classification tools such as uncertainty tables, decision-mapping, and multi-criteria analysis to help integrate knowledge between disciplines and across social and physical sciences. They review a range of deliberative techniques for assessing risk and uncertainty in an interdisciplinary manner (including integrated assessments, mediated modelling, expert elicitation, narrative approaches, and community participation methods). In addition, they highlight that social science "*should* … add to our understanding of natural hazard risks and uncertainty" (emphasis original, p. 503), stating how the cultural and epistemological differences between physical and social scientists create a particular communication challenge, discussed next.

4.2.1. The challenge of epistemic divides

Effective participatory dialogue type approaches require an appreciation of the different epistemic cultures present between disciplines and between scientists and operational decision-makers, as well as their different 'models' of science. Twelve (11%) documents discussed this in the context of shared communication and uncertainty management (see Table 12). A key issue is that the current deficit model of communicating science (assuming your audience lacks the relevant knowledge) creates an epistemic divide between experts and stakeholders and a division of labour as to what simplifications are appropriate [100]. Deitrick and Wentz [116] review the different uncertainties that arise between scientific researchers and policy makers, from knowledge-production based in the former, to solutions-oriented in the latter, and highlight how an awareness of this difference is vital for effective communication. Incorporating epistemic cultural differences into classification and management schemes is important, especially considering scientists will aim to reduce epistemic uncertainty while, for example, engineers accept uncertainty exists due to it being at the core of innovation and invention and can represent sources of solutions to many engineering problems [56]. For example, in the context of ensemble flood forecasters, such different epistemic cultures between scientists and different stakeholders (meteorologists, flood forecasts, the public, etc.) can result in different tolerances for uncertainty in decision making [50]. This can result in a 'duality of error' regarding false alarms, where flood forecasters would change the threshold to decrease false alarms due to the impact they have on response of the public to future warnings. This however increases the chance of 'false negatives' (unwarned floods). In comparison, meteorologists prefer to reduce those false negatives at the expense of increasing false alarms. Thus, a system of shared uncertainty management between different scientists within a modelling and forecast chain must acknowledge and account for differences such as these.

When considering the development of shared uncertainty management approaches to model based decision-making, Grubler et al. [97] state that epistemic differences can actually affect the initial problem formulation, particularly because the different world views of natural and social scientists result in 'linguistic uncertainty' due to a lack of a common language. In particular, the different systems of scientific enquiry adopted in different disciplines, ranging from analytic, empirical, synthetic, or conflictual models of enquiry, lead to a different emphasis on language in the initial problem formulation. As stated by Stirling [98] "the intrinsically plural, conditional nature of knowledge [should be recognised, so that] science advice can become more rigorous, robust and democratically accountable" (p. 1029). They argue that adopting a pluralistic and conditional approach enables a debate on broader questions and can provide a basis for a "more-equal partnership between social and natural science in policy advice" (p. 1031), and help to resolve polarized debates about science in policy by integrating quantitative and qualitative approaches across disciplines. This is particularly relevant for disasters when science advisory group processes require both disciplines to formally provide advice together [2], with each being characterised by fundamentally different epistemologies and ways of defining 'science', different processes of knowledge creation, and different ways of defining what is an 'objective' or 'true' representation of the world as defined by their 'epistemic culture' [163] (see also [155]). However, Stirling [98] cautions that this pluralistic conditional approach to manage uncertainty will not remove the deep intractability of the many uncertainties present, the perils of group dynamics, or the perturbing effects of power on communication and uncertain science advice; rather it makes them more rigorously explicit and democratically accountable.

To address these epistemic divides, Shackley and Wynne [47] suggest science advisors act as a bridge between scientists and policy makers in climate change management, employing 'boundary-ordering devices' to help facilitate the communication and shared understanding between the worlds of science and policy. They suggest 6 types of boundary objects to help achieve order between science and policy, as follows: 1) the clarification and management of uncertainty [which we note could utilise the typology type schemes discussed above], 2) the reduction of uncertainty, 3) the transformation of uncertainty (e.g. changing indeterminacy and ignorance to uncertainty and risk), 4) condensation of uncertainty (collapsing multi-layered/multi-faceted uncertainty into one aggregated uncertainty to provide control to external audiences, but not offend peers); 5) scheduling into future (identifying how and when key uncertainties will be reduced, see also Moss [140]); and 6) the displacement of uncertainty (placing responsibility for that uncertainty in another discipline, domain or social world - so that uncertainty ceases to threaten the authority of the scientific community). van Pelt et al. [117] investigate the use of a simulation game as another type of boundary object to bridge epistemic divides and communicate climate change to water managers tasked with adaptation. They demonstrated an increased general understanding of uncertainties, but not however a statistically significant different understanding in learning, or understanding for the specific uncertainty they aimed to improve with the game (natural variability).

The appropriate choice of boundary object would depend on the time scale and time pressures of the science advice and decision-making context under consideration. However, whether short or long time scales, the goal should be to develop relationships and communication frameworks during preparedness and mitigation type activities that enable these pluralistic principles to be followed in high pressure short time situations, even if the boundary objects themselves cannot be employed at that time. In addition, such activities should work towards enhancing both scientists and decision-makers understanding of each other's information needs, tasks, responsibilities and demands via the development of shared 'mental models' of the response environment (discussed in Sections 4.2.2 and 7). These can be developed through team building, cross training, and scenario planning tools [2,164–167].

Epistemic divides are discussed by Rabinovich and Morton [54] as one of the reasons why people may not act on a message or information in the manner expected by a science advisor. People are not just influenced by the framing of the message, but also by their prior expectation of the message. Such an expectation is framed by whether they assume a classical model of science (which considers science to be the 'search for truth'), or a Kuhnian model of science (which considers 'science as debate'). In the Kuhnian approach [168], actions are less likely to be undeterred by uncertainty and uncertainty may actually increase motivations. Rabinovich and Morton [54] attributes this difference to trust, where people with a Kuhnian model of science trust a message more if it includes uncertainty because it matches their expectations, whereas a classicist distrusts such a message as they search for absolute truth rather than relative certainty and "the very presence of uncertainty … is not consistent with their view of what good science should be" (p. 999). They thus suggest the importance of assessing the beliefs of an audience and adapting communications accordingly. Such an approach is thus important to consider when adopting the translatory discourse and participatory type approaches described previously for the development of shared uncertainty management decision-makers (see Section 4.2 above). In a public communication arena, Rabinovich and Morton [54] thus suggest that communicators should prepare the public for the levels of uncertainty prevalent in contemporary science, and present it as a deeper understanding of the subject rather than a shortfall. Maxim and Mansier [115] present a discussion of similar issues, outlining how people reference their 'science model' (which can include hypothesis, disciplines, subjectivity, etc.) to interpret the science and uncertainty present and assess the credibility of any information. They state that individuals also reference non-scientific sources encountered in their daily life, their personal considerations about the world, similar information previously encountered from another source, and how it aligns to knowledge from school or professional experience. Including these aspects in the framing or process of a communication or dialogue is similar to that of accounting for an individual's 'mental models', discussed in Section 4.2.2 below.

Finally, when considering epistemic differences, and alternative models of science, the role of post-modern approaches to science communication and uncertainty management, such as post-normal science, was raised by a number of documents [67,86,115], with many referencing the work of Funtowicz and Ravetz [158,161]. Such an approach is more reflective, and moves beyond just the quantitative tools inherent to uncertainty analysis (e.g. sensitivity analysis or Monte-Carlo type simulations) to consider the mass of uncertainties that include technical, methodological, epistemological, and societal dimensions [86]. The post-normal science approach acknowledges that 'facts are uncertain, values are in dispute, the stakes are high and decisions urgent' [161], particularly when these uncertainties are of an epistemological or ethical kind. This approach recognises that risks are interpreted and managed subjectively. Funtowicz and Ravetz [161] propose problem-solving frameworks that account for this plurality of perspectives, including uncertainty, value loading, community values, history, personal experiences and other forms of 'non-traditional' science information. It is this philosophy that underlies the transparent system of notations provided by the NUSAP (Numeral, Unit, Spread, Assessment and Pedigree) [153] to express and integrate the different types of uncertainty including quality and values, rather than 'banish' uncertainty from science [see 161]. This NUSAP approach forms the basis for the Netherlands Environmental Assessment Agency's Guidance for Uncertainty Assessment and Communication reviewed in van der Sluijs et al., [86], the pedigree analysis and pedigree matrix developed by Kloprogge et al. [76,88], discussed further in Section 4.1, and the communication protocol of Fischoff and Davis [99] (see also [67,69]). Since Funtowicz and Ravetz [161], a number of other philosophies and approaches have been developed to account for such plurality e.g., [162], which have been adopted in a range of contexts, particularly under conditions of uncertainty, including: the use of cultural theory, transdisciplinary studies, future studies, action research, and policy sciences (see [12,160,169]).

4.2.2. The effect of an individual's world view

Seven (6%) of the documents (Table 12), highlighted the role an individual's model of the world and science has on perceptions of scientific uncertainty. Maxim and Mansier [115] state that individuals interpret information based upon their 'science model'. Budescu et al. [53] found that interpretations of verbal statements varied depending upon ideologies and beliefs in climate change. Tak et al. [118] concluded from an empirical study into the visualisation of uncertainty in temperature forecasts that in the absence of any textual explanation of an uncertainty range, people will apply their own internal model of the uncertainty distribution that often closely resembles a normal (cumulative) distribution. Such internal models of 'the way things are' do not just affect the information receiver's perception of the information, and subsequent actions, but also the communicator.

As discussed by Portnoy et al. [102] the perception that doctors have of the ambiguity aversion of their patients (which may be erroneous or biased) can impact their communication of uncertainty, even unintentionally. It is thus important to be cognisant of such affects when considering the dialogue between scientists and decision-makers, or science advisors communicating between scientists and policy makers, particularly during engagement and participatory approaches. Adopting transparent and clear uncertainty documentation via systems like typologies enables decision-makers to engage with the level of uncertainty appropriate to their needs (as discussed in 4.1.2). An example of such an approach to counteract the potential biases and misconceptions is provided by Slavin et al. [119], who developed an uncertainty visualisation method that follows the Carnegie Mellon mental models approach [170] to uncertainty communication. This involves 1) creating an expert model of the problem, 2) characterising the audience in terms of their mental models for perceiving risk, and 3) creating communication materials that address the misconceptions in step 2 and "provide normatively accurate information for accurate risk perceptions" [119; p. 75].

Politi and Street [93] advocate that for doctors to effectively communicate uncertainty to their patients they need to enhance a 'shared mind' with them, to facilitate collaborative decision making and action plans. They provide strategies and steps to achieve this shared mind that are also relevant to any engagement or participatory process involved in uncertainty management, and include: providing clear explanations, checking for understanding, eliciting the recipient's values, concerns, needs, finding common ground, reaching consensus on a plan, and establishing a mutually acceptable follow-up plan to help facilitate any collaborative decision making. In their discussion of the benefits of such participatory type approaches, Patt and Dessai [11] identify that the most effective approach is one that "incorporates an awareness of decision heuristics and framing into a participatory and distributed decision-support system, anticipating the potential for 'cognitive conflicts' between the communicators and the users of the information" (p.430). This is similar to the 'mental models' communication approach of Morgan et al. [170], which highlights the need to understand the world views of different stakeholders to facilitate effective communication, where an individual's mental models are their "representation or visualisation of a real system, including concepts, relationships, and their role within that system" [2].

4.2.3. Ethics

Four (4%) documents considered in detail the ethical issues in communicating uncertainty (see Table 12). Keohane et al. [82] reviewed the communication norms regarding honesty in reporting conclusions, as well as the social and financial contract scientists have to inform society and government.[1] Citing the work of Onara O'Neill [171] they state that communication is "ethically acceptable only when it aims to be accessible to and assessable by its audiences" [82; p.350]. Thus, they outline five ethical principles to communicating science under uncertainty, including: 1) honesty, 2) precision, 3) audience relevance, 4) process transparency, and 5) specification of uncertainty about conclusions. Regarding the uncertainty inherent in modelling in particular, they state that there are no generally agreed rules for assessing and reporting it, but that ethically both parameter and structural uncertainty should be communicated. However, this can be in conflict with the ethical code for 'audience relevance', which in turn can be in conflict with precision, and process transparency. They conclude that ethically the goal should always be to lead an audience to understand the range of likelihoods of future possibilities, and how their decisions affect the future, stating that by not including uncertainties a communicator will mislead their audience. Finally, they see "[no] ethical principle supporting the highlighting of the quantifiable aspects of uncertainty over the non-quantifiable aspects" [82; p. 361-362], advocating for the more transparent communication of subjective uncertainties via elicitation of subjective expert opinion and development of an additional assessment table that communicates the "range of such judgements and their aggregation (or not) into a scientific consensus" (p. 361). Other approaches to communicating these subjective uncertainties include the post-normal approaches based on that proposed by Funtowicz and Ravetz [161,172], which involve problem-solving frameworks and incorporate typologies and categorisations that account for and communicate the plurality of perspectives including quality and values see [67,69,76,86,88]; discussed in Section 4.1 and Section 4.2.1. For example, Kloprogge et al. [88] develop a pedigree matrix that incorporates the value-ladenness of assumptions including practical aspects, epistemic, disciplinary-bound epistemic, and socio-political issues.

Han [85] present an interesting discussion of both the benefits and harms of communicating uncertainty in a clinical setting, asking whether communicating uncertainty actually enhances or diminishes patient autonomy. Considering harms, they discuss how ambiguity aversion could deter protective behaviours if the efficacy of such behaviours has a degree of uncertainty. They also emphasize how ambiguity about a risk estimate can increase risk perceptions, worry and pessimistic judgements, leading to avoidance of beneficial interventions. They highlight how communicating uncertainty can reduce satisfactions with a decision, as it introduces doubt as to whether the right decision has been made. They conclude that the answer may not be to tailor communication according to a patients' tolerance of uncertainty, but rather to provide patients with the support needed to increase uncertainty tolerance, via a patient-centred approach which adopts standardized language and methods to represent and communicate uncertainty. While these operational recommendations relate to doctor-patient decision making, they are very relevant to science-stakeholder or agency decision making; ethically, the focus should centre on decision-makers and involve communication which is flexible and matches end-user uncertainty needs and tolerance. This is best achieved through participatory dialogues (Section 4.2), which enhance the autonomy of the decision-maker see also [82,120,173].

When considering such participatory or dialogue type approaches, the role of different perspectives on ethics between disciplines and world views thus becomes important. Austin et al. [120], discussed the different ethical standards inherent to different disciplines involved in communicating scientific uncertainty, including science/risk assessors, law, and journalism which results in different priorities for communication. There are thus social and ethical value judgments in all forms of science, and philosophers have identified that science has normative value based judgments in it, that can not necessarily be separated from epistemic issues [121]. Considering climate science, Winsberg [121] states that value judgments occur in methodological choices, optimization, metrics of success, problem solving, and evaluations, concluding that the value judgments are woven into these complex models, and discuss how this process may include inherent biases stakeholders themselves are unaware of (e.g., it being impossible to remove social and ethical values from forecast predictions). Winsberg thus suggests that uncertainty quantification can act as a communication tool as it attempts to separate epistemic from normative issues, and divides intellectual labour by leaving the normative value laden considerations to political decision-makers; except that we can never really remove all the normative value issues from the science we communicate as it is inherent within it.

4.2.4. Trust

Five (5% Table 12) documents talked in depth about the role of trust in communication. Joslyn and LeClerc [113] report the finding that including uncertainty information increased both trust and concern, primarily because individuals have intuitions about uncertainty present in a system, and mistrustful when it is not communicated. However, Markon and Lemyre [114] argued that trust is not systematically affected by the mention of uncertainty, and that communication of diverse sources in a risk message did not affect trust in government, but divergence between experts or conflict in the data could. They thus suggest that a message should be precise about the sources of uncertainty involved, and how to effectively present disagreements between experts in a way that does not minimize the message or credibility, rather than conceal or downplay them. Wiedemann et al. [23] highlight the connection between trust and ethics, where the audiences' evaluation of the speakers' credibility, their trust in them, their perception about their motivation, degree of accountability, and supposed goals, affects their perception of the message. Any previous experience of a message or messenger is thus persuasive and difficult to change. Thus new uncertainty information may collide with experience-based beliefs. Non-experts can thus have difficulties differentiating among different types of uncertainty and drawing conclusions, and thus Wiedemann et al. [23] state that it is the expert's job to help non-experts make informed judgments.

While most papers indicate communicating uncertainty is preferable, Longman et al. [60] discuss how large uncertainty ranges lead to decreases in perceived credibility. This is in contrast to previous studies that find it increases perceptions of honesty, enhances decision making efficacy, and increases credibility (for example [174]). For this, Longman et al. [60] consider credibility to encompass honesty, trust, accuracy, fairness, unbiased, and telling the complete story, and reason that this decrease in credibility may be due to people expecting experts to provide knowledge of a precise nature in their field of expertise, and misinterpreting the uncertainty as evasiveness or lack of knowledge. This relates closely to how an individual's 'model' of what science is, or their mental model or map of the issues of importance and the relationships between them, can impact uncertainty perceptions (see also Section 4.2.2). As discussed by Maxim and Mansier [115], people reference such models when interpreting science and uncertainty, and this model can include not just the science itself but also non-scientific aspects such as their model of science, how they trust science itself, and their previous experience of a message or source, as well as the credibility or trust they have in that source.

[1] For example, in NZ, universities (and their scientists and academics) are legally described in clause 162 of the Education Act of 1989 to be 'a repository of knowledge and expertise' that accepts 'a role as critic and conscience of society' that 'advances, disseminates, and assists the application of, knowledge'. (http://www.legislation.govt.nz/act/public/1989/0080/latest/DLM183668.html; accessed 1st September 2018).

4.3. Techniques for communicating specific or complex uncertainties

The previous sections have focused on the approaches to create an environment for effective communication. Considering our initial core questions (Table 2), several challenges were identified regarding complexities ranging from communicating ensemble models and expert knowledge through to how to communicate specific uncertainties, such as probabilities. A number of selected documents explored these in relation to model confidence and bias (Section 4.3.1), consensus and dissensus (Section 4.3.2), ensemble communications (Section 4.3.4), and spatial visualisation of uncertainty (Section 4.3.4).

As listed in Table 12, numerous papers discussed the effective visualisation of uncertainty via graphs, tables and images (9 documents, 8%), communication of probabilities (18 documents, 16%), and communicating time frames and time dependent information (12 documents, 11%). Key lessons from these three themes are briefly summarised in Appendix A, and we highlight here the point raised by both Aven and Renn [101] and Han [85] that probability is often erroneously used to describe all uncertainty. This is an issue when communicating probabilities, as they thus do not usually include other epistemological, structural uncertainties, and value judgements, nor alternative definitions of risk and different understandings of probability (see Section 4.1). For time-dependent information, we also note that communicators should consider well-specified questions and provide information over an appropriate range of **decision-relevant** time frames, including information on *when the uncertainty may be reduced* [18,140,144]. A number of typologies include time and uncertainty related to time in their frameworks [87,89,106], which can provide a way to communicate time dependence. However, no articles investigated the effective communication of information in different time frames of a crisis (short near term vs. longer response or recovery time frames), and we suggest this important issue be a subject of future research.

4.3.1. Model confidence and bias

A key issue in model uncertainty communication concerns model confidence, and the weighting or choice of model used. This becomes particularly important for multi- or ensemble models as each is biased by the value judgments and assumptions that informed the development of the model [121]. Thirteen documents (12%, Table 12) consider this issue in depth.

A primary suggestion is to include a scale of the confidence in a model, or the choice or potential biases in a model, as one of the categories in the overall typology developed for an uncertainty quantification and communication [56], as discussed in Section 4.1. Secondly, a number of documents recommend or advocated for the use of ‘confidence guidelines’ to communicate the level of confidence in a model [24,25,148]. In the guidance for the lead authors of the IPCC fifth assessment report on the consistent treatment of uncertainties, Mastrandrea and Field [24] include a metric for the communication of the confidence in the validity of a finding, based on the type, amount, quality and consistency of evidence (e.g. mechanistic understanding, theory, data, models, expert judgment), and the degree of agreement. This confidence is expressed qualitatively via a confidence scale chart that relates level of evidence and level of agreement across available evidence and models.

Busch et al. [148] utilise this IPCC approach in the context of ocean acidification and highlight the importance of evaluating and communicating this state of knowledge. Gill et al. [25] recommend the use of confidence indices in the definition of sources of forecast uncertainty, as part of the World Meteorological Office communication guidelines, citing as an example the approach of the Swiss Federal Office of Meteorology and Climatology who use a reliability measure in their weather forecasts. Other techniques for communicating levels of confidence, and the grading of quality of evidence can be found in Han [85], who outlines approaches used for medical and clinical evidence. These include formal qualitative rating schemes that grade the quality of evidence according to key sources of ambiguity, including: inconsistency, imprecision, indirectness (limited generalizability and applicability) of results, and methodological problems that lead to bias.

However, the use of such guidelines or judgements of confidence can represent another source of value judgement and add another level of bias to the process [79,101,140,141]. Risbey and Kandlikar [141] highlight that earlier IPCC approaches that utilised confidence needed to include a quantitative scale to avoid ambiguity, but that the use of a 2 dimensional scale that considers likelihood and confidence (as still advocated for in Mastrandrea and Field [24]), creates contradictory combinations such as an “extremely likely low confidence” event. They state that "this could result in a bias towards expressing results with higher confidence, since it is meaningful with this scheme to present only statements associated with higher confidence“ [141]. They thus present an alternative approach that provides a mechanism for making explicit the reasons for low or high confidence based upon assessments of data quality and scientific knowledge.

Moss [140] also discusses the IPCC approach advocated by Mastrandrea and Field [24] identifying that the lead chapter authors were actually uncomfortable quantifying their subjective judgments, preferring to consider uncertainty in qualitatively objective terms. They state that the IPCC approach failed to ‘harmonize the “confidence” language’ [140], resulting in the confusion between the use of these confidence levels, and other qualitative levels of understanding outlined in the IPCC guidance note, as well as causing confusion between the confidence scale and the quantitative likelihood scales used for translating numerical probabilities into verbal terms (see also Appendix A). They highlight that adopting intuitive approaches to rating confidence is subject “to a variety of biases, including ambiguity, probability weighting towards the centre of a distribution, and context dependency” [140; p. 650], particularly when using qualitative rather than numerical terms. They review various experiments that have investigated the approach taken by the IPCC and demonstrated the interpretation biases that can occur when using confidence and likelihood ratings (see also [11,81,175]). Such evaluation is vital as it helps identify ways to minimize such effects and ensure the effective use of the “rigorous and insightful methodology” provided by these expert elicitation methods [140; p. 656]. Evaluation is thus not just necessary for public communication products, but also for the communication terms and tools used by science advisors and decision-makers within an assessment process (discussed further in Section 4.5, see also [176]).

Aven and Renn [101] reiterate the issue of the difficulties in quantifying estimates of confidence, and the poor and subjective use of the recommended confidence scales in the actual IPCC assessment reports themselves. Supporting our discussion in Sections 4.1 and 4.2, they state the importance of communicating a “clear distinction between the model concepts and their estimations” (p. 10) to ensure the structure and scientific quality of the uncertainty analysis. They conclude that the IPCC guidance note is not sufficiently precise on this and that communicating our confidence or degree of beliefs in models of uncertainty is subject to its own uncertainty that also needs to be communicated. Additional assumptions made during this process should also be communicated [88], and the sensitivity of any decisions to such assumptions explored [157]. Additionally, Adler and Hirsch Hadorn [79] question how to conceptually distinguish between agreement, evidence, and consistency in the IPCC's confidence scale, or whether they are appropriate concepts to be considered for the purpose of developing a confidence scale. They see this as particularly challenging as this scale lacks the ability to identify areas of ignorance or controversy. This need to communicate the full range of values and bias in the confidence of a model, or the scientific evidence, or in the model choice itself, is further highlighted by similar discussions by Kloprogge et al. [88], Wesselink et al. [94], and Demeritt et al. [50] (see also Section 4.1). As discussed by Demeritt et al. [50] such transparent communication is vital due to a ‘certainty trough’ whereby people can place undue confidence in models because they fail to appreciate the judgements and construction of uncertainty associated with that model.

4.3.2. Consensus and dissensus

In their thorough review of 39 articles that discuss and critique the IPCC's treatment of uncertainties, Adler and Hirsch Hadorn [79] highlight that the procedure used to attribute a degree of certainty in scientific information (via likelihood and confidence scales) is reliant on consensus among the lead authors, and is subject to diverse value judgments of evidence. Thus, there is a need to develop a better way to report on dissensus among experts, and to represent and interpret evidence. They suggest that the answer is to move away from dissensus on a particular position, 'towards consensus on a plurality of relevant, even controversial positions or findings, as assessment results for users' (p. 674). They state that such an approach accounts for the purpose of consensus (to reach inter-subjectivity), limits where consensus may be mistaken, and can be adaptive within alternative decision-making frameworks.

We found that 10 (9%, Table 12) of our reviewed documents also discussed consensus. Busch et al. [148] support the approach of the IPCC and its use of confidence scales to incorporate consensus levels of evidence and levels of agreement. They state that particular challenges arise when working in an interdisciplinary space, where different disciplinary perspectives can exist as to what constitutes certainty. This can present particular difficulties for decision-makers, particularly if one discipline identifies something as certain and another very uncertain, resulting in delayed action when 'good' science may be interpreted as too 'unsettled' to warrant timely action. Busch et al. [148] thus state that transparent non-persuasive communication which promotes informed decision-making where all uncertainty is acknowledged, should focus on how certain we are as "decision-makers are more interested in whether potential consequences are adverse enough or certain enough to justify the costs of action" (p. 37). Alternatively, Budescu et al. [81] recommends that "communication of uncertainty should be refined by conveying differential levels of uncertainty that reflect the degree of consensus (or lack thereof) about the reliability and quality of the available scientific evidence" (p. 306), similar to Risbey and Kandlikar [141].

Stirling [98] state that it is unclear whether communicating consensus or not is most accurate or useful for policy, highlighting that communicating the array of contrasting specialist views and reasons for different interpretations is more consistent with scientific rigour and "democratic accountability" (p. 1030). They suggest the use of more plural and conditional methods for science advice, via tools such as their uncertainty matrix (discussed in Section 4.1). We note however, that how this is accommodated and utilised by recipients needs to be investigated further, given the political and economic biases that can affect interpretation and use of such contingent information. Keohane et al. [82] advocate that scientists must thus find ways of more precisely explaining the "levels of consensus that characterizes a particular claim, even if it is not a claim that they particularly as individuals wish to advance" (p. 361), as there is no ethical argument for communicating "only conclusions that command a consensus" (p. 362). When there is no consensus, Keohane et al. [82] state that it is superior to provide a range of possible results, with a statement explicitly stating that there is great uncertainty about these propositions. Oppenheimer et al. [74] raise the important related concept of 'premature consensus' which can occur when all the uncertainties are not adequately accounted for, particularly the structural model uncertainties. We note that this is more likely when the process is driven by external pressures, including political imperatives. Such uncertainties indicate less is known than the numerical forecast model estimates may suggest, and thus they advocate for more transparency of all uncertainties, including giving poorly understood phenomena and quantifiable uncertainties more equal weighting.

The results of Markon and Lemyre [114] underscore the complexity of communicating dissensus, particularly when communicating to the public. They found that communicating a divergence between experts (representing ambiguity in advice), or conflict in the data (representing epistemic uncertainty), can null the influence of an advisory warning (see also [21]). Different sources of uncertainty were found to affect adherence to warnings differently, and sharing a lack of data did not result in a downplaying of the message. They thus recommend that public agencies should be precise about the source of uncertainty, and not conceal or downplay existing disagreements between experts. Rather there is a need to identify better ways to present this to the public in a way that "does not minimize the agency's message and credibility" [114; p.1119]. These findings are similar to that of Patt [64] who investigated the effect of conflict-based versus model-based framing of uncertainty on action choice and timing, finding that while there was no precise distinction between these two uncertainties in terms of action, the way in which they were framed in a message did matter. Thus they recommend that advisory panels should "pay close attention to the social features of uncertainty, such as conflict between experts" ([64], p. 37), and should communicate both the quantitative and qualitative aspects of uncertainty, as any conflict that has arisen "about particular estimates of the future may signal features not only of the science, but also of the politics of that science, [which] are relevant for decision-makers" ([64], p. 45).

Thus, Markon and Lemyre [114] suggest that communicators should explain not just that a divergence exists between experts, but should elaborate further on the nature of the disagreements, such that "citizens feel more empowered and better able to forge their opinion on the subject" (p. 1119). However, this itself creates a dilemma. Firstly, it is important that this process is preceded by attempts to develop a shared mental model that develops understanding of advisors and decision-makers different world views, epistemologies, needs and demands (discussed further in Section 4.2; see also Doyle and Paton [9]), otherwise such advice may activate pre-existing mental models including biases, and political and economic imperatives that could intensify rather than ameliorate conflict. Secondly, as discussed by Moss [140], different subjective expert interpretations of model results, and the lack of methods for aggregating different expert characterizations of uncertainty, can provide "an opportunity for special interests to confuse and divert public discourse" (p. 643). They thus suggest more use of expert elicitation techniques in the IPCC and other climate assessment processes would enable more accurate and open uncertainty assessment and communication. They highlight that concerns that such expert elicitation methods make "knowledge seem more conditional" (p. 656) and subjective are limiting the application of this useful methodology. However, as discussed by O'Hagan et al. [177] all modelling involves human decisions that are ultimately subjective, such that "all statistical methods, classical/frequentist or Bayesian with either non-informative priors or expert opinion priors, have some amount of subjectivity within them" (p. 199) (see also Aspinall [178], Donovan et al. [179], and Donovan et al. [180]).

Several expert elicitation approaches exist. These range from simple averaging of opinions, through to the Delphi method (see [177,181]), and on to more advanced mathematically based pooling approaches where experts are weighted differentially according to ratings of their performance expertise [e.g. 181,182], which can be both objective or subjective. Aspinall [183] adopted the Cooke approach to provide structured elicitation for probabilistic volcanic hazard assessment (see also [184,185]). Alternative non-statistical approaches include the recent work of Dessai et al. [186] that utilised expert elicitation to build qualitative narratives of future regional rainfall change, and physically plausible evolutions of future regional climate.

4.3.3. Ensemble communication

Fifteen of the selected documents (14%, Table 12) explicitly discussed issues arising due to communicating ensemble model outputs, one of our core questions (Table 2). These include issues around perceptions of the ensemble models, challenges of communicating them, and the misunderstanding of uncertainty and biases that ensue [50,58,59,68,121,142]. Other examples and case studies of ensemble communications were found [51,65,66,92,108,109,145,147]. These include transforming the ensemble forecasts into a single deterministic forecast time line with uncertainty [92], an aggregate visualisation plot of ensemble outputs (which explore the input data and parameter space) which incorporates uncertainty via a probability that a threshold is exceeded [108], the use of colour coded frequency figures to help interpret ensemble outputs for flood inundation models [51], and a novel form of a box plot to display ensemble weather forecasts outputs [66].

A popular technique for ensemble communications is the use of 'spaghetti plots' particularly for forecasts. In these, the output variable is plotted on a chart for each model through time allowing for a comparison of results and an assessment of the range of possible outcomes. However, both van der Zwaag et al. [145] and Bruen et al. [147] discuss the communication issues with these spaghetti plots, which can become very confusing as high number of ensembles are included. They state that there is no universally preferred method to communicating ensemble forecasts, and that regular meetings should be held with users to enhance the use of uncertainty information. Examples of conveying ensemble data via a range of different spaghetti plots and other charts can also be found in Tak et al. [118] and in the World Meteorological Guidelines [25].

Bruen et al. [147] review alternatives to these ensemble spaghetti plots, such as dividing the forecasted variable or uncertainty into bands or warning levels, colour-coded by the forecaster. van der Zwaag [145] suggests 3 techniques for flood mapping that could be used as alternatives. These include a) alpha blending (where each ensemble is rendered with transparency and overlain, resulting in the most opaque portion of the graph representing the highest probability of inundation), b) box and whisker plots in 2D, 3D that include cross sections, profile views, and plan views, and c) colour mapping. However, they stress that many of these methods have not been evaluated and that there is an imperative need for evaluation of ensemble communications, as discussed in Section 4.4.

A particular challenge with forecasts that utilise the output of many alternative models combined into ensemble models, is the identification of one of these forecasts as the 'best' for a forecast which is then often communicated without the uncertainty representing the spread in the range of models. Winkler [146] highlights that this was a particular issue during Storm Juno in January 2015, where a worst-case scenario forecast was issued based upon the output of a single (European) model forecast which had the best track record to date. The uncertainty based on the other multiple model forecasts was not communicated. When this worst-case scenario did not eventuate, there were high costs involved to New York City financially, and to the credibility and reputation of the National Weather Service forecasters. The latter was compounded by the fact that the Weather Channel updated their forecast as new evidence came in, adapting their choice of model resulting in a more accurate forecast. Winkler [146] state that the issue here is not necessarily the choice of model forecast used, but rather the lack of communication about the uncertainty in that forecast.

Parker [68] point out that ensemble models (particularly those based on Monte Carlo type approaches) are challenged by the high dimensionality of uncertainty due to the larger initial condition uncertainty space than non-ensemble models, as well as the computational intensity and structural uncertainty issues. They highlight how probability density functions are not always appropriate to display the uncertainty of ensemble outputs due to high structural or epistemic uncertainties. In those cases they suggest the use of alternatives such as the likelihood a value will fall in a range, the expected sign change, or the change of magnitude. Building on this, Parker [58] argues that interpretation of ensemble results in climate change modelling in political and public spheres can be problematic, indicating that while ensemble models provide a lower bound on response uncertainty, they do not provide an upper bound as they do not explore structural, parametric, and initial condition uncertainty, which is often misunderstood. Thus, the practice of transforming ensembles to precise probabilistic estimates of uncertainty can be problematic because these uncertainties and assumptions made in model development and choice are not considered or communicated. Parker [58] makes the point that decision-makers may thus make poorer decisions than would have been made had these other 'second-order' uncertainties and assumptions been more apparent. These second order uncertainties include assumptions and judgments in the models, and the value-ladenness behind them (relating to practical, epistemic, political, and socio-political issues), which could be communicated via the Kloprogge et al. [88] pedigree matrix (see Section 4.1). Demeritt et al. [50] also identified that flood forecasters didn't fully understand the uncertainty around the mean of an ensemble prediction system, or how to use it. However, in contrast, when uncertainty was provided in the form of a standard error around a point forecast for a suite of ensemble weather temperature forecasts, Roulston et al. [142] found that decisions improved.

This relates to the discussion of Winsberg [121], who argues that ensemble models are often erroneously considered a 'conceptually coherent set' when transformed into precise estimates, because current methods assume all models within an ensemble are equally good, or that they can actually be weighted, or that the ensemble models represent a sample of independent draws from all available. However, the choice of models used can be subject to bias, some may be weaker in terms of performance and validity than others, and each are full of value judgments due to the various social and ethical values and assumptions made throughout. They suggest that Bayesian expert elicitation to separate epistemic from normative aspects of the models used would help enhance communication by enabling more accurate uncertainty quantification (see also Aspinall and Cooke [185] and O'Hagan [177]).

4.3.4. *Effective visualisation of uncertainty: mapping, spatial, and GIS*

Numerous papers (29, 26%, Table 12) consider techniques and approaches for the visualisation of spatial uncertainty, with a focus on maps and GIS. They discuss the range of different media and methods available [10,25,48], the range of decision-maker perspectives and understanding related to their prior knowledge and numeracy [127], whether visualisation actually enhances decision making [128], issues with probability shading colour schemes and biases [129], as well as display issues [103] in terms of how much information to include in a single image or display. Two documents [109,130] discuss in detail the technical and numerical aspects of employing visualisation options.

To explain the available uncertainty visualisation techniques described by these documents in depth would be beyond the scope of this paper. However, of particular use for future natural hazard communication endeavours are those documents that summarise the range of different approaches available to incorporate uncertainty into a map or GIS [10,48,77,103–107,109,118,122–124]. These include the modification of 'free graphical variables' [107] or 'intrinsic graphic properties' [118] which can be varied by focus, clarity, fuzziness, transparency, crispness, colours, size, position and angle; the addition of 'extrinsic information' via graphical, geometric objects or glyphs which can be altered by colour, size and symbology; and the use of animation such as blinking regions, blinking pixels, or blinking objects. Other general cartographic techniques that can be altered include isosurface rendering, lighting, blurring, shading, contours, contour format, colour schemes, saturation, hue, opacity, pseudo-colouring and texture. Blurring and similar techniques can be described as an 'image discontinuity' technique [105]. Such approaches and techniques can then be classified by their appropriateness for communicating scalar, vector, or multivalue uncertainty [10,48]

In addition to the visual depiction of uncertainty, Griethe and Schumann [107] state that uncertainty can be communicated using other human senses, such as acoustic, touch, and vibration. However, they argue that studies that adopt this approach often only focus on a single uncertainty value and may not be appropriate for abstract data, or that very few consider it for visualising ‘error, precision and validity at the same time’ (p .31). Bearman et al. [133] suggest the novel use of sonification and evaluates the use of sound to represent uncertainty (see https://player.vimeo.com/video/37252584 for an example), finding better user performance when sound is used rather than simple visual systems [see also 48,77]. Examples of various uncertainty visualisation techniques in use can be found in Nadav-Greenberg et al. [131], Beven et al. [111], Gould et al. [91], Gill et al. [25], Retchless [132]; and the technical aspects of developing such visualisations in Bastin et al. [130].

A particularly interesting issue for a hazard forecast situation is whether uncertainty is better visualised in a series of separate maps, or in a single combined map [91,103,125]. The former approach can be considered to be ‘univariate’ (comparing one map for data to another for uncertainty) and the latter ‘bivariate’ [103]. In the bivariate approach, uncertainty is displayed via the extrinsic techniques described above (adding geometry to symbols, etc.) or intrinsic approaches (where the visual variable of a symbol is modified, such as colour shading). Through an empirical study, Kubíček and Šašinka [125] identify that maps combined (bivariate) encourages parallel processing of data, while separate maps (univariate) encourages serial processing as information has to be held in memory to enable a comparison between maps. The former resulted in quicker decisions, but more inaccuracies for complex tasks. The latter resulted in slower but more accurate decisions.

Similar to the issue of maps combined or separate, several documents review the different static and dynamic approaches to displaying uncertainty in maps [72,116,126]. Kunz et al. [103] discuss the benefits of interactive cartographic information systems due to their ability for users to interactively query and drill down into the relevant data. This expands on the work of MacEachren et al. (as cited in Bostrom et al. [62]) who identify that intrinsic representation (changing the appearance of an object) is better for communicating overall uncertainty, while extrinsic representations (using additional symbols) are more suitable for specific locational uncertainty. Similar to MacEachren, Deitrick and Wentz [116] state that techniques can be classified into ‘visually integral’ approaches (where one alters the data symbology so both the data and the uncertainty are represented by a single variable), or ‘visually separable’ approaches (where patterns, textures or geometric objects that depict uncertainty are overlain on the map). They find that in general, evaluation demonstrates that decision-makers prefer visually integral maps due to the simpler image produced, while researchers prefer visually separable images which allow them to identify and evaluate the uncertainty. We also direct readers to the systematic review of geospatial uncertainty visualisation by Kinkeldey et al. [187], found separate to our systematic search, within which they discuss five ‘dichotomous categories’ for uncertainty visualisation expressions and properties, including 1) explicit/implicit; 2 2) intrinsic/extrinsic; 3) visually integral/separable; 4) coincident/adjacent; and 5) static/dynamic. They advocate for a systematisation of future empirical studies on uncertainty visualisation, and recommend a move towards user-centred task-oriented uncertainty visualisation typologies (see also Sections 4.1.1 and 4.1.2).

Different user preferences highlight the need to tailor communication techniques to audience needs (see Section 4.2). Pang [10] explore this further by identifying an approach to communicating uncertainty defined as ‘task-oriented visual mapping’ (p. 282–283), where they state that it is not possible to develop a one-size-fits-all approach to a hazard communication due to the many stakeholders, different needs, and users. As discussed in Sections 4.1 and 4.2, there is a need to develop schemes that address both the communication issue at hand and is tailored to the needs of the decision-maker [71,77,99]. Pang [10] proposes a framework which identifies *types of users* (scientists, engineers, doctors; policy makers, decision-makers, court cases; operational users; casual users), *types of tasks* (analysis; monitoring; exploration, data mining; persuasion, communication), and *types of data* (data dimensionality; data type; multivariate data; multi-value; ordinal, categorical, cardinal). Through this framework “different visualisation methods can be used to match the needs of a particular user, task and data combination” (p. 285). This is vital as any information presentation should be simplified to the core needs such that it does “not overload the cognitive tasks” of the decision-maker (p. 282), enabling users to focus on the important aspects of the data.

Appropriate use of such uncertainty visualisation techniques is particularly challenging. There is a danger that sophisticated visualisation methods and graphics could misrepresent the data, where the design used to graphically represent information can intentionally or unintentionally mislead, over-simplify, overload, or misrepresent a message (see reviews in [188,189]). Thus, the visualisation technique used must be theoretically justified by the data [72]. There is a trade-off between the appeal of visualisation media and the correctness of information which of itself can result in additional ‘uncertainties in visualisation’ [122]. Griethe and Schumann [107] thus recommend that communicators first reduce the complexity by focusing on the data and uncertainty relevant to the decision, rather than to try and visualise everything It is also vital to evaluate the visualisation method chosen [190], to ensure the communication meets it’s intended objectives (discussed further in Section 4.5). Unfortunately there is a lack of such evaluation of uncertainty visualisations, as discussed by both Brus and Svobodova [106] and Tak et al. [118]. This results in both a lack of understanding as to what constitutes effective visualisation communication, as well as uncertainty as to which visual communication strategy is most appropriate for different contexts and audiences, discussed next.

4.4. Evaluation

The lack of evaluation of uncertainty visualisation techniques is raised by 8 (Table 12, 7 %) of the documents in our review [62,105,106,116,118,123,128,134], who highlight that we cannot continue to develop and use new techniques if we do not know how useful the visualisation of uncertainty actually is for decision making. As stated by Tak et al. [118], there is no “comprehensive understanding of the parameters that influence successful uncertainty visualisation” (p. 6). Thus, it is vital that one tests interpretations of uncertainty visualisations prior to dissemination, as the intentions of a designer do not necessarily match interpretations of the viewer, particularly as perceived uncertainty does not necessarily map linearly to visual features. Found separately to our selected papers, both Fisher [190] and Rohrmann [176] also discuss in depth the need for empirical evaluation to ensure a communication meets its intended objectives, to prove its effectiveness, to facilitate the improvement of future communication, to identify context specific approaches, and to provide an empirical basis to choose between different communication strategies. In addition, Rohrmann [176] highlight that “intuitive assessments of … effectiveness can easily fail because of wrong cause-effect attributions” (p. 172). Thus, through empirical evaluation of communication we can aim to identify the true cause of any miscommunication.

From our selected papers, Hope and Hunter [134] argue that when evaluating the representation of uncertainty in GIS data, it is not just the comprehension of the information we should be assessing, but the impact that visualisation has upon decisions, which is currently severely understudied. They present a cautionary tale supporting the need for empirical evaluation of ‘best practice’ communication recommendations. They empirically found that the presence of uncertainty information in GIS output actually lead to “irrational decisions being made” (p. 199), whereby people made unexpected decisions due to a misunderstanding of, or due to the influence of, the way the uncertainty itself was presented (rather than the uncertainty values themselves). They thus state that attention should be paid towards how we visually present the data as the presentation itself can affect decisions. This is similar to the 'framing' affects that have been identified through extensive investigations into text based messaging, where two objectively equivalent statements worded differently can result in different actions (see reviews in [18,139,191,192]). Hope and Hunter [134] highlight that most studies of visualisation and representation of GIS data focus on the extra cognitive demands the visualisations place on decision-makers (whether users can cope with the additional information), and less on how the representations themselves affect the decision being made. To date, much research into effective techniques for communication have been identified as those that do not detract from the accuracy or speed of decision, or ones which users rate as easiest to understand and use, however Hope and Hunter [134] draw attention to a need to consider how the uncertainty information impacts the outcome and efficacy of the decision itself. The importance of this was reiterated by Broad et al.'s [193] and Tak et al.'s [118] discussion of how the public misunderstand hurricane forecast track maps and the areas at risk (see also Section 4.3.4). While these visualisations describe the most likely path of the central eye of the storm, and a cone depicting the range of its possible tracks, many people assume the cone actually depicts the full width and extent of the hurricane itself and fail to understand the hurricane can actually impact a much larger area outside the cone.

Examples of evaluation processes for a communicated product can be found via cases studies [128], the brief survey tool presented [123], or the empirical approaches used to test particular visualisation techniques (such as [125,127,129,131,134]). Bonneau et al. [105] provide a review of available evaluation techniques, including theoretical evaluation (identifying whether a map follows graphical design principles), low level visual evaluation via psychometric visual user studies, and finally via task oriented user studies, providing examples from medical, weather and climate, and security and intelligence. Bostrom et al. [62] reiterate that there are not enough empirical studies to evaluate the techniques, and future research should focus on evaluation and understanding rather than developing more of these techniques. Based on existing research they thus identify five measures for the effectiveness of cartographic visualisations of risk and uncertainty, including: 1) accuracy and congruence, 2) accessibility, 3) retention, 4) change in perceived risk, and 5) subjective measures of quality and usefulness; measures which should also be considered for general risk visualisations and communications of model outputs. Additional evaluation examples can be found beyond our reviewed papers in the fields of communicating risk and warning design (e.g., [194,195]) and health emergencies (e.g., [196]). While these are considering a different communication challenge to our focus here, the process by which they conduct their evaluations provide important lessons for the evaluations of the communication of model uncertainty. We also direct readers to the recommendations of Kinkeldey et al. [187,197], found since our systematic search, who also identify a lack of systematic evaluation strategies, and highlight the need for research to "better understand the process of working with information on uncertainty as a basis for subsequent studies of its visualisation" [197; p. 18], highlighting a need for 'task-centred typologies and guidelines' [187; p. 385] as well as a "typology of uncertainty representations" that defines "categories of reasoning tasks or decisions that uncertainty could make a difference for" [197; p. 19].

5. Existing guidelines and recommendations, and key lessons from this review

Twenty of the selected documents (18%, Table 12) conclude with some clear specified recommendations for the communication of modelling uncertainty, model related uncertainty, or the suite of uncertainties associated with a risk analysis or model assessment, that are of particular relevance to our core questions. An additional 4 documents (4%) contained specific agency guidelines for the Netherlands Environmental Assessment Agency [76], the World Meteorological office [25], and for the IPCC assessment reports [24,150]. Eight documents (7%, Table 12) contain recommendations based upon a critique or experimental review of the IPCC approach, alongside a further 3 who critique the IPCC guidelines [79,141,148], but don't generate specific guidelines themselves. From these, key cross-cutting issues can be identified, including:

- That it is vital to acknowledge the uncertainties, and the specific type and nature and sources of uncertainty [25,81,84,101,132] to assist the effectiveness of decision making;
- The need to communicate more than just the scientific and technical uncertainty, but also the 'social history of uncertainty' and to solicit social science expertise in communications [64,140], which can include communicating explicitly the potential value-ladenness of assumptions in a risk or model assessment [88];
- The importance of understanding a decision-makers perspective and needs to facilitate effective communication [84,85,93,132,137,140]. To which we add the importance of understanding the social and organisational context and capabilities of decision-makers, which can impact their interpretations of uncertainty information [9];
- The need to also communicate *when* the identified uncertainties can be reduced in the future [81,140];
- The importance of traceable accounts to describe evaluations of evidence and identification of uncertainties [24,150];
- The need to standardize the language and methods used to represent and communicate uncertainty [24,85,150], while remembering disciplinary, context, and individual differences in understanding that will affect the appropriate terminology to use [11,81,84]. This includes the need to recognise that 'science for policy' is a different enterprise to 'science' itself due to its need to be responsive to policymakers' needs [150];
- Specific recommendations for ways to represent individual uncertainties linguistically or visually [11,24,25,72,76,81,94,132,137,139,150];
- The need to communicate the degree of confidence in a particular analysis [24,56,101,150], or to communicate the range of assessments and the confidence experts have in them to represent the range of views, [e.g., 94];
- The importance of evaluating the communications of uncertainty, and using empirically tested approaches wherever possible, [e.g., 24,84,137,140].

Hyden et al. [149] reference a number of other specific organisational guidelines recently developed, including the Joint Committee for Guides in Meteorology and their Guide to the Expression of Uncertainty in Measurement, as well as the Seventh Framework programme approach to communicating uncertainty for the Open Geospatial Consortium via a standard 'markup' language called UncertML. We recommend future research should consider a search targeted at finding and summarising the existing recommendations across international organisations. While some of these recommendations have been developed for non-natural hazard settings [e.g., 84,85,93], the lessons they identify are very valuable for the natural hazard model uncertainty communications we are considering here. Beyond the literature surveyed here, a number of books also provide further lessons for the communication and analysis of uncertainty in the natural hazards, including Rougier et al. [198], Riley et al. [199], Crichton et al. [200], and Bammer and Smithson [201], and we direct readers to those for further reading. In particular, Rougier [202] and Rougier and Beven [203], respectively review frameworks for representing aleatory uncertainty in terms of probabilities, and a framework for epistemic uncertainty. In addition, Beven et al. [157] outline methods to quantify epistemic uncertainties, such that the impact of assumptions upon decisions can be examined, enabling the communication of uncertainty estimates, discussed further here in Section 7.

5.1. Key lessons from this meta-synthesis

The key themes and lessons drawn from our review of the literature supplement the above existing recommendations, and cut across our initial core questions, as follows:

- The use of the term '**model related uncertainty**' to encompass the full range of uncertainties throughout the modelling process (from defining the problem, through to computational issues, initial conditions, verification, and beyond), helps to avoid the confusion when 'model uncertainty' is sometimes used in the literature to represent 'structural uncertainty' (see Section 3.1).
- A **typology** system guides a scientist communicator through a process of identifying and classifying, articulating and prioritising critical uncertainties, and knowing what to communicate. It prevents the assumption that the statistical output provides a comprehensive account of uncertainty (including interdependencies). By specifying sources of uncertainty, scientists can also set realistic expectations about whether these uncertainties can be reduced in the future, when, and how best to include them in analyses.
- The choice of **typology** system depends on the context, and there are many general systems (Section 4.1) and systems developed specifically for visualisation and geospatial uncertainty (Section 4.1.1) to choose from. Multiple typologies may be required for individual decisions or throughout the process
- Typology schemes can facilitate communication by bridging **epistemological** and cultural differences between disciplines, by creating a system of shared uncertainty management that acknowledges and accounts for their different priorities and perspectives, recognises the conditional nature of knowledge, and provides for a more equal partnership between social and natural science in advice.
- Typology schemes should be developed through an **engagement or elicitation approach** to develop a mutual understanding between scientists and decision-makers of the relevant uncertainties that must be assessed and communicated for their decision needs. Science advisers can act as a bridge to facilitate this understanding. Through engagement, a typology system can be advanced by including scores for the qualification of the knowledge base and for the value-ladenness of any assumptions, as well as the value-ladenness inherent to practical aspects, epistemic, disciplinary-bound epistemic, and socio-political issues.
- Adopting an engagement process supports scientists in meeting the decision making process of respective users, creating credible and legitimate two-way participatory type communications, where the depth of scientific uncertainty analysis is decided upon with the operational decision-makers and led by their decision-making needs. It also enables the development of shared mental models, which help scientists and decision-makers make complementary contributions to the management of complex, evolving events. These models include the process under consideration, representations or visualisations of the system, its concepts, relationships, and the role of model factors within that system.
- For such engagement and participatory approaches to work, a code of practice and professional guidelines must be developed to encompass the uncertainty estimation and translational discourse, which considers funding, leadership and **ethical** standards which can vary significantly between different disciplines. This should accommodate the five ethical principles to communicating science under uncertainty, including: 1) honesty, 2) precision, 3) audience relevance, 4) process transparency, and 5) specification of uncertainty about conclusions (see also [82]). To this can be added a need to support decision-makers to increase uncertainty tolerance [85].
- Ethically the focus of the communication of model uncertainty should be on **decision-maker centredness** which is flexible and matches their uncertainty needs and tolerance, and is best achieved through participatory or two-way type dialogues. Uncertainty identification and quantification (through a typology approach) can thus act as a communication tool as it attempts to separate epistemic from normative issues and divides intellectual labour by leaving the normative value laden considerations to the political decision-makers.

Considering the technical aspects of communicating complex uncertainties, we summarise that:

- For **ensemble models**, we found no overall recommended approach to communication, and recommend that user and decision-maker preference and **evaluation** is vital to identify the appropriate approach. Several documents present examples of the different approaches (see Section 4.3.3) and solutions to specific communication challenges.
- For **model confidence,** a scale of the confidence in a model, or the choice or potential biases in a model, should be included as one of the categories in the overall typology developed for an uncertainty quantification and communication. This is particularly important when we consider that each model is biased by the value judgments that went in to the development of the model, and the various assumptions made along the way. This can be built upon 'confidence guidelines' to communicate the level of confidence. Such a scale can be a qualitative rating scheme rather than quantitative, and grade the quality of evidence according to key sources of ambiguity, including: inconsistency, imprecision, indirectness (limited generalizability and applicability) of results, and methodological problems that lead to bias. We recognise however the important point that such guidelines or judgements of confidence are seen themselves to add in another level of bias and value judgments that themselves need to be evaluated and acknowledged.
- A key challenge identified was the reliance on **consensus** amongst scientists [and models] to form advice, and the difficulties communicating conflict between experts. Thus, there is a need to develop a better way to report dissensus. Scientists can incorporate consensus and dissensus into a typology framework to communicate the array of contrasting specialist views and reasons for different interpretations, which is more consistent with scientific rigour and "democratic accountability". By communicating conflict about future estimates, scientists also indicate features of the science, and the politics of that science, which are also relevant for decision-makers.
- When visualising uncertainty, the focus must be on the data and uncertainty relevant to the decision. There is thus a need to adapt the communication to the **context** and the decision-maker, and to **evaluate** such communications whether they are being used in a typology based participatory type communication scheme or not [64].
- There is a lack of **evaluation** of uncertainty communication approaches, particularly when using visualisation techniques. Evaluation studies should be prioritised in future research, with a particular focus on the link between visualisation and decision making. This is important not only to ensure that producers and users are making comparable interpretations and applications of uncertainty, but also that the communication is being used as intended.

Thinking of these lessons in the context of the wider issue of communicating general uncertainty, we note that thirteen of our reviewed documents (12%, Table 12), discussed these general issues beyond model uncertainty that are also of relevance. Leung et al. [151] highlight the importance of tailoring communications to suit the socio-political context, and to acknowledge socio-political and other perspectives that can arise between social and natural science in uncertain advice, via a plural approach to communication [98] which provides a basis for a more equal partnership. This requires a high level of transparency and an understanding of receivers' needs, where what is communicated (in level of detail and level of quantification) depends on the needs of the audience or partner [135]. Research by Morss et al. [143] demonstrates that receivers (or partners) are keen to receive such uncertainty, so long as supplementary and context details are included to enhance understanding and confidence. For such a partnership to be successful, communicators and scientists in turn desire more information about the user uncertainty requirements and training as to how to actually communicate uncertainty [59].

Such a partnership approach to uncertainty communication advances upon the 1949 deficit model of risk communication (reviewed by Markon and Lemyre [114]), and builds upon the more recent models that acknowledge people are not irrational when they respond differently, due to risk being dependent on individual, social and cultural values (see also [7]). A strategic and partnership approach to communication has more emphasis on consultation than persuasion, where transparency is key, and the public and decision-makers are partners in a constructive dialogue around risk (described as a 'strategic risk communication model' [114]). Key to this increased transparency is the expectation that sources of uncertainty are acknowledged, and the need to be more precise about the source of uncertainty involved to improve decision-making and trust [114]. This is particularly important, as if individuals have an intuition about uncertainty being present and it is not included in a communication, it can severely damage their trust in the communication and source [113].

Developing such partnerships, and understanding needs prior to communication, such that trust and confidence is increased is of particular importance as model complexity increases. Future models will have wider, not narrower, uncertainty due to the added complexities and cascading uncertainties [144]. Thus, scientists will appear to know less not more, creating a particular communication problem that requires new transparent communication strategies. There is also the potential for extreme negative impacts if uncertainty is not included. For example, the 2008 United States financial crisis has been linked to a failure to communicate and understand model uncertainty, and a lack of understanding of the model, resulting in financial firms "vastly underestimating systematic risk" [149; p. 1094, 204]. By omitting uncertainty from communications, we may actually be disempowering decision-makers. This is highlighted by Wiedemann et al. [23] who state that the underlying cognitive framework that empowers people to make informed judgments should be considered more when developing risk communication. For example, the effects of uncertainty on decision making behaviour have been found to be mediated through feelings of efficacy, and when a positive rather than a negative frame was used in uncertain scenarios (highlighting possibility of losses not materializing) stronger intentions to act were identified [152].

6. Limitations and future research

As discussed in the methodology, this literature review's goal was to identify the dominant themes and constructs from across a range of literature that was selected through a targeted search criteria, based on core questions, and selectively sampled through inclusion, exclusion, and relevance criteria [37,41]. We did not aim to capture and describe or critique the entire body of relevant literature on this topic through an exhaustive comprehensive review, as this would have been a significant challenge given the extremely large body of literature. There are thus some limitations to the review presented here, mainly that important and relevant texts may have been missed in our key word search, or omitted through the relevance scoring and filtering process (which was based only on abstracts). We thus recommend that future research conduct more comprehensive critical reviews of each individual theme identified here, including further research into the efficacy and practicality of approaches recommended by the literature (e.g. through empirical investigations or via case studies), particularly given that these approaches must be accommodated and utilised by recipients where political, economic, social, and organisational biases can affect interpretation and use. Other limitations in this study include the time between the date of our search, and publication. As we are not aiming for an exhaustive review, any additional sources found after our search were introduced as 'secondary sources' by being raised as comparative texts to further explore issues identified and discussed in the 'primary sources'.

The themes discussed herein have been identified by holistically drawing from lessons across a full range of complex situations, disciplines, and a range of decision-making situations (in terms of scope and time). Thus, future research should consider how these core lessons should be tailored or adapted for more specific decision-making situations, ranging from short-time high pressure response scenarios through to longer-time mitigation decisions, as well as to explore the efficacy and practicality of the approaches across different contexts. For example, how do we adopt a decision-relevant needs assessment process for a communication within a high-pressure time dependent inter-agency wide response vs. a longer term readiness communication between two individuals representing their respective agencies? As discussed in Section 3, our literature has also not answered how to communicate the propagation of uncertainty, as literature found for this question focused on the very technical aspects of its calculation rather than its communication. However, by adopting a typology approach that identifies all the uncertainties, this propagating uncertainty should be accounted for. In addition to this, our review was not able to address a number of other questions, which we suggest should be the subject of future reviews, including:

- The effective communication of information in different time frames of a crisis (short near term vs. longer response or recovery time frames), and how model uncertainty communications in one phase of emergency management (e.g. readiness) will influence those in another (response and recovery).
- How to communicate the role of time, and what visualisation approaches are most effective for different time scales (short, medium, long, time dependent).
- The role of the precautionary principle, and cognitive biases, on what model uncertainties a scientist chooses to communicate.
- How the specific type of model (physical, probabilistic, insurance, etc.) affects the communication of uncertainty.
- How to communicate model performance in low data situations, model selection, and the role of the expert in uncertainty assessments.
- How cultural characteristics (such as different levels of uncertainty avoidance and power distance, and different individual and organisational values of science) impact the recommendations made herein, and the appropriateness of them across different cultures.

Finally, we recommend that future reviews should consider a search targeted at finding and summarising the existing recommendations across all international organisations, and reiterate the conclusions of Bostrom et al. [62] that future research should focus on evaluation of communication techniques and visualisation, rather than developing more of them, focusing in particular on how their format affects decision making.

7. Conclusions

Modelling, and the insights provided by numerical models, are vital for natural hazard risk management and response. Communicating the uncertainty inherent to these hazard models, their outputs, and the hazard modelling process is a challenging task. Currently there is no clear recommended approach to address these issues, even though there is a growing appetite and expectation amongst operational decision-makers for the communication of uncertainty to help facilitate effective decisions in hazard settings. We found that the majority of literature on uncertainty communication focuses primarily on the need to disclose uncertainties rather than the technical process of how to do so. However, through our systematic thematic review of 111 publications, we find a dominant message: *Fundamental to the effective communication of uncertainty is to first understand the needs of the decision-maker. Scientists should then concentrate efforts on evaluating and communicating the uncertainties relevant to those specific decision needs and time frames, rather than communicate all uncertainties which can overwhelm a communication and decision making process.* For this to be effective, scientists, communicators and other stakeholders should actively collaborate with users to co-develop typologies or taxonomies of uncertainties suitable for their needs and the hazard modelling and communication situation, including how events evolve over time. They should adopt participatory and engagement-based approaches to the co-development, production and application of information management systems such as these to support decision making procedures (see Doyle and Paton [9]). This is particularly important for evolving events where uncertainty is also an implicit component of the operating environment, and where the management of uncertainty has scientific, political, economic and social implications.

It is the process of engagement in the development of information and uncertainty typology schemes, as well as their use, that is critical to effective communication, management and prioritisation of uncertainties [47,67,69,71,99,110,111]. Through this scientists can move towards a 'shared management' of uncertainty [50,56,97] which acknowledges and accounts for the different priorities and perspectives in a decision making process, including different degrees of analysis depending on the decision requirements. A typology could be adapted from one of the many available in the existing literature (see Section 4.1), to enable the identification of all uncertainties and a prioritisation of those for estimation and communication, depending upon their impact on decisions. Typologies should be developed in partnership with decision-makers to ensure the prioritisation of uncertainties considers their decision needs (see Section 4.2). We also envision that some complex or cascading hazards may require multiple typology systems to categorise the uncertainty at the different stages of the assessment and communication processes. Such an approach should consider the different epistemological perspectives inherent to this uncertainty, as well as the value ladenness of any assumptions and judgements (e.g., [88] see Section 4.1 and Section 4.2.1).

The goal is thus to identify which uncertainties are most relevant to respective end users, and will have the greatest impact on their decision making, such that resources and efforts can be concentrated on reducing and communicating them. Through the engagement process scientists should thus aim to communicate the complete story of uncertainty, including its social, historical, quantitative and qualitative aspects [64]. Ideally such engagement with decision-makers, and the use of tools such as typologies, should be included from the outset of model development and communication, and tested and used at all stages in the risk management cycle and associated DRR planning activities. However, in time limited situations where such a framework or typology does not exist, the principles of a typology outlined here could still be used to guide the systematic categorisation and communication of decision-relevant uncertainties, as far as is possible under the crisis situation. Such an approach is thus designed to meet the needs of individual audiences, and move beyond the unsuccessful one-size-fits-all approaches to communication (see also [10]).

The development of one (or many) typologies in a model or risk assessment limits the risk of the accidental omission of uncertainties interacting to create escalating uncertainties. Further, given that some level of uncertainty will always be present in response and risk assessment settings and the development of more complex and comprehensive hazard models will increase both the existence of and knowledge of uncertainties [144], the process of developing such typologies with decision-makers can help increase uncertainty tolerance, uncertainty literacy, and uncertainty familiarity with users.

We acknowledge the ability to develop a typology with decision-makers depends upon a number of factors, including capacity and resources; different priorities, politics and agendas; as well as other barriers to collaboration including trust, transparency and partner equity [9,205–207]. As discussed by Kloprogge et al. [88], a typology or pedigree matrix should be used in situations where the assumptions and uncertainties impact the decisions and policy the most. The above processes and suggestions also assume that scientists and users are engaging from the beginning of model development. However, in many cases we will be drawing from existing available models. We thus conclude with a proposed framework for 'effective practice' in the communication of ***decision-relevant*** model related uncertainties in a situation where time and resources allow for effective engagement. For an existing model, this involves:

1. The systematic identification of all uncertainties in the model, calibration data, and any layers, including assumptions and the potential value-ladenness of those assumptions [88].
2. Rating of these uncertainties on two potential scales: a) the degree to which they will affect the simulated model outcomes or calculations, and b) how well they can currently be addressed.
3. Categorisation of these uncertainties into a typology (or multiple), using one of the schemes presented in Section 4.1.
4. Collaboration with users and decision-makers to rank uncertainties and assumptions in terms of how they affect their specific decisions, considering both risk management, response, and recovery, as appropriate.
5. Collaboratively decide which uncertainties and assumptions to concentrate evaluation and communication efforts upon.
6. For the prioritised uncertainties, quantify, propagate, analyse, and communicate following best practice communication guidance (see Section 4.3), using empirically evaluated methods if possible (acknowledging that many visual best practice methods have not actually been evaluated, Section 4.4).
7. Evaluate the communication for efficacy and audience needs, and adapt as appropriate for future communications.

For situations where a model or analysis process has not yet been developed, the above process can be prefaced by engaging with users earlier to identify a needs based modelling approach, which utilises the simplest models to adequately solve their problems, acknowledging that increasing model complexity will increase uncertainties. This relates to the framework of Beven et al. [157] for good practice in natural hazards modelling, which includes 1) establishing the purpose of the risk analysis, 2) evaluating available data, 3) eliciting opinions about sources of uncertainty, 3) choosing methodologies for correct analysis, 4) conducting sensitivity analysis to explore how those identified uncertainties impact decisions, and 5) communicating the meaning of the uncertainty analysis through a condition tree or audit trail, including visualising the outcomes (p.2).

Fundamental to the framework we propose here, is the importance of identifying with decision-makers what the ***decision-relevant*** uncertainties are, and focusing analysis and communication upon those. To identify these, the elicitation and sensitivity analysis approach outlined by Beven et al. [157] above could be employed, or the 'task-oriented visual mapping' of Pang [10]. In addition, it may be helpful to employ scenario planning tools to develop potential 'futures' that accurately reconcile the needs, goals, and expectations of diverse agencies [2,164–167]. These could also use qualitative expert elicitation processes that provide narratives of future scenarios, as demonstrated by Dessai et al. [186] for climate change.

Collaborative exercises and simulations can also be used to scope out the potential information needs and decision time frames, and to develop similar mental models of the communication task at hand [2,9, 208–213]. A collaborative approach thus aims to overcome the lack of ownership of uncertainty inherent to one way communications, and by adopting a 'translational discourse' [69] a joint decision about which uncertainties should be modelled, evaluated, and communicated can be made. This goal will be enhanced by further research to "understand how different decision-makers conceptualize uncertainty for specific domains" [116]. Further, by participating in such activities, decision-makers and scientists can develop a greater understanding of each other's operational uncertainties, such as those arising from economic, social, and political influences [9].

In addition, by utilising techniques inherent to the mental model approach for participatory communication [214], differences between the natural hazard scientists and decision-makers understandings of the model can be identified, to help facilitate more effective discussions in the development of a shared **decision-relevant** typology of the uncertainties related to natural hazard models. Such an approach thus aims to ensure that our advice follows the ethical principle of 'audience relevance' [82,171], is 'useful, useable, and used' [215,216], and 'socially responsible' [217] in terms of societal goals and values, where the "transparent information and involvement of stakeholders during the research process can mitigate uncertainties and risks and is a morally responsible action" (p. 4). This is further supported by Benessia and De Marchi [218] who show contradictions, controversies and conflicts are bound to arise when expert advice is communicated with an "improper reduction of the overall situational uncertainty to its scientific component only", particularly when it is analysed in isolation from ethical, political, and societal concerns (p. 35).

Acknowledgments

EEHD was supported by funding from The Earthquake Commission | Kōmihana Rūwhenua and GNS Science | Te Pū Ao 2014–2016, the Ministry of Business, Innovation & Employment National Science Challenges: Resilience to Nature's Challenges | Kia manawaroa – NgāĀkina o Te Ao Tūroa 2016–2019, and partially supported by QuakeCoRE | Te Hiranga Rū – Aotearoa NZ Centre for Earthquake Resilience 2018, a New Zealand Tertiary Education Commission-funded Centre. This is QuakeCoRE publication number 0342. EEHD also thanks many colleagues for fruitful discussions that helped shape the thinking behind the initial questions driving this literature review, including: Matt Gerstenberger, Nick Horspool, Mark Stirling, Sally Potter, Sara McBride, Jacqueline Dohaney, Wendy Saunders, Elspeth Tilley, and Mary Anne Thompson, as well as many members of the eSocSci | Hui Rangahau Tahi Communication Research and Natural Hazards Network, Aotearoa NZ. We thank three anonymous reviewers who provided valuable comments that improved this manuscript.

Appendix A

Brief summary of key lessons relating to the themes on effective visualisation of uncertainty via graphs, tables and images (9 documents, 8%), communication of probabilities (18 documents, 16%), and communicating time frames and time dependent information (12 documents, 11%).

Study	Key Lessons
Effective visualisation of graphs, tables, and images – note many have not been empirically evaluated	
Bostrom et al. [62]	• Outline various methods for visualising seismic risk and uncertainty, including a review of individual techniques and the effects they have on comprehension. • Considers risk ladders, stick and facial figures, statistical graphs, line graphs, dots, pie charts, histograms, attributes (such as colour, interactivity, animation, and texture), 2D and 3D issues, and virtual reality.
Pappenberger et al. [57]	• Conducted an empirical study to identify what formats experts like to use to communicate probabilities at a single location visually. Recommends a list of approaches. • User preference is not sufficient to choose an appropriate technique, and more research is needed to identify actual comprehension aspects for content and visualisation types.
Loucks [135]	• Considers visualisation of risk magnitude. Presents different graph and table methods for illustrating uncertainty. • Communicators must listen and learn from their stakeholders in order to craft effective risk messages and communications that better reflect "the perspectives, technical knowledge, and concerns of the audience" (p. 50) [see also 10].
Marimo et al. [136]	• Participants made decisions faster when presented with a graph rather than a table of uncertainty information. • Preferences and interpretation accuracy is context dependent.
Tak et al. [118]	• Presents interesting methods for conveying ensemble data via spaghetti plots and other charts.
Gill et al. [25]	• World Meteorological Guidelines - Lists various example visualisation displays.
Potter et al. [66]	• Present an 'advanced box plot' to combine uncertainty data, which incorporates an abbreviated box plot, histogram, moment data (mean and stdev, skew, kurtosis, tailing), and distribution fitting, and propose a way to adapt it to 2D data.
Slavin et al. [119]	• Present an interactive approach that adapts a risk and uncertainty visualisation based upon the risk perception of the user, utilising the mental models approach of Morgan et al. [170]. Uses the user's perceptions to create individualised visualisations for perceived risk and uncertainty, addressing their misconceptions and providing normatively accurate information.
Probabilities (see also reviews in Doyle et al. [18,139]).	
Bostrom et al. [137], Budescu et al. [53], Handmer and Proudley [52]. Marimo et al. [136], Moss [140], Risbey and Kanlikar [141], Spiegelhalter et al. [73], Van Steenbergen et al. [138]	• Focus on the issues of framing and misinterpretations of verbal likelihood statements and numerical probabilistic statements.
Budescu et al. [53], Budescu et al. [81], Doyle et al. [139], Gill et al. [25], Mastrandrea and Field [24]	• The use of translation tables to help facilitate consistent use of verbal terms.
Gill et al. [25], Spiegelhalter et al. [73], Thompson et al. [129]	• The use of probability statements alongside probabilistic map representations.
Budescu et al. [81], Han et al. [61], Longman et al. [60], Patt and Dessai [11]	• Consider the communication of point and range probabilities and uncertainty bounds around probabilities, and how people interpret or act upon them.

Spiegelhalter et al. [73]	• Present a wide range of examples for how to communicate probabilities visually, including bar charts, pie graphs, and methods for portraying proportional representation and continuous quantities - fan charts, probability distributions, roulette wheels, uncertainty intervals, map based uncertainty, and infographics.
Communicating time dependent advice and different timeframes	
Moss [140]	• To communicate forecasts effectively to policy and decision-makers, communicators should focus on well-specified questions and decisions and 'provide information on the prospects for reducing uncertainty on decision-relevant time frames' (p. 656) (see also Doyle et al. [18]).
Maslin [144]	• States that scientists should focus on communicating *when* not *if* a threshold limit will be reached, such that the focus of the uncertainty is on *when* not *if* – to increase actions and constructive dialogue about mitigating decisions.
van Steenbergen [138]	• Graphical time dependent forecast communications found to be better for forecast professionals and their decisions. • Linguistic communication is more suited to "communicate to the larger public" (p. 104).
Doyle et al. [139]	• Communicators must be consistent with the use of linguistic terms that describe time (e.g. "within the next X days" vs "in the X next days) due to their statistically significant different interpretations.
Laurent et al. [92]	• Considers how to communicate uncertainty with a time component via an ensemble flood forecast time line graph that includes uncertainty.
Nadav-Greenberg [131]	• Investigates wind speed maps that use a box plot of predictions at specific times and locations.
Roulston [142]	• Investigated decisions made dependent upon weather forecast temperatures over time.
Joslyn and LeClerc [113]	• Empirical studies found that people anticipated an increase in uncertainty as the lead-time increases.
Morss et al. [143]	• Found people's confidence decreased in a forecast as the lead time increased. However, participants still preferred to receive forecasts with uncertainty than not, depending on the context and local experience of forecasts and subsequent weather.
Höllermann and Evers [89], Ekström et al. [87], Brus and Svobodova [106]	• Consider time, and uncertainty related to time, in their typology frameworks. In particular, Höllermann and Evers [89] consider how the uncertainties change in different time frames for flood risk management, including response, medium and long term uncertainties.

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