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From scientific models to decisions: exploring uncertainty communication gaps between scientists and decision-makers

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Abstract

Effective communication of uncertainty relies on transparent exchanges between scientists and decision-makers. However, significant gaps often exist between how scientists and decision-makers perceive, understand, and communicate uncertainty. This study examines the dynamics of uncertainty communication between scientists and decision-makers, employing a reflective thematic analysis of 32 interview datasets, comprising 17 scientists and 15 decision-makers. Our results show that Scientists typically approach uncertainty through methodological rigour, employing technical vocabulary and probabilistic language, which aligns with their scientific training but often complicates comprehension for decision-makers. Conversely, decision-makers prioritise actionable insights and practical implications, requiring uncertainty to be communicated in a way that supports decision-making processes across diverse contexts. The study further highlights the need for tailored communication strategies that bridge the complexities of uncertainty with the practical needs of decision-makers, emphasising collaboration and user-focused uncertainty visualisations as pathways to enhance uncertainty communication between scientists and decision-makers for the uptake of uncertainty information into decision-making.

Keywords Uncertainty communication · Decision-making · Scientific models · Scientists

1 Introduction

In a world increasingly threatened by disasters, effectively communicating uncertainty in decision-making is crucial (Doyle et al. 2018; Lammers et al. 2024; Schneider 2016; Spiegelhalter 2017). Whether predicting the path of a cyclone (Broad et al. 2007) or estimating the flood probabilities (Leskens et al. 2014), decision-making often centres on the uncertainty that lies in scientific models (Smith et al. 2016). Uncertainty communication, conveying 'where the scientific models are wrong about reality' (Sterman 2002) lies at the heart of the interaction between scientists, who generate the data, and decision-makers, who must act upon it.

Although significant efforts have been made to enhance uncertainty communication (Spiegelhalter 2017; Walker et al. 2003; Kwakkel et al. 2010), significant gaps persist, leading to miscommunication between scientists and decision-makers. Krisper et al. (2019) highlight that the core issue in communication lies in how information is transmitted between the sender and the receiver, represented here by scientists and decision-makers, respectively. The challenge also lies in bridging the gap between scientific understanding and the perception of the receiver (Krisper et al. 2019; Rosenbaum 2015). Since science plays a vital role in informing decision-making, addressing this communication gap is critical for effectively integrating scientific insights into decision processes (Doyle et al. 2019; Van Der Bles et al. 2019; Lucchesi et al. 2021). Understanding how scientists and decision-makers perceive uncertainty communication helps bridge this gap, allowing for more tailored communication strategies (Lammers et al. 2024; Lilburne et al. 2022; Steel et al. 2009a; Kuhnert et al. 2018).

The interaction between scientists and decision-makers is complex. Scientists, often working in small teams and relying on models, hesitate to communicate uncertainty, particularly when unsure of how decision-makers will interpret it (Leskens et al. 2014; Fischhoff 2012). Decision-makers, representing diverse stakeholders, seek information on uncertainty to support their decision-making, although the

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level of detail required varies by context (Doyle and Paton 2018; Doyle et al. 2019). Scientists commonly use confidence bounds or probabilistic ranges to express uncertainty (Spiegelhalter and Hauke 2011; Quigley et al. 2019), aiming to provide decision-makers with a sense of reliability and precision (Budescu et al. 2012; Uusitalo et al. 2015). However, an overreliance on probability can be problematic since decision-makers often struggle to interpret complex probabilistic information (Handmer and Proudley 2007; Doyle et al. 2014; Budescu et al. 2014; Bayraktarli et al. 2011; De Bruin et al. 2000). Furthermore, variations in scientific literacy influence decision-makers' ability to understand probabilistic models (Constable et al. 2022; Padilla et al. 2021a, b). Addressing these challenges can enhance the communication of uncertainty in decision-making, particularly in cases, such as Disaster Risk Management (DRM) (Schneider 2016).

Probabilistic methods are a long-established standard in uncertainty communication (Budescu et al. 2014; Winter et al. 2018; Miran et al. 2019). However, when scientists communicate with non-scientists, these standards may need to be better understood. Research suggests that the effectiveness of information in decision-making depends mainly on the characteristics and capabilities of the receiver (Constable et al. 2022; Doyle et al. 2018; Padilla et al. 2021a, b; Quigley et al. 2019). This discrepancy makes it challenging to communicate scientific uncertainties to audiences with varying levels of scientific literacy.

Decision-making, as in the case of DRM, occurs in real-world conditions, independent of the scientific models developed to understand them (Frigg and Hartmann 2021). The way uncertainty is communicated influences decision-makers' perception and interpretation of science (Hoss & Fischbeck 2016; S. Schneider 2016), ultimately shaping policies and planning decisions (Cradock-Henry et al. 2023; Höllermann and Evers 2017; Horita et al. 2017). Scientific models help decision-makers conceptualise future scenarios, but they are constrained by their limited capacity to represent reality (Wit, van den Heuvel, and Romeijn 2012). Despite their limitations, models remain invaluable tools, as they structure complex data and facilitate exploration of potential outcomes (Walker et al. 2003; Kwakkel et al. 2010; Horita et al. 2017; Leskens et al. 2014; Webley et al. 2016). However, their practical application depends on effectively communicating their limitations, assumptions, and outputs, ensuring that decision-makers can interpret and use them appropriately.

Understanding the communication barriers between scientists and decision-makers is crucial for enhancing effective communication (Doyle et al. 2018; Schneider 2016). This requires structured comparisons to identify and resolve misunderstandings, fostering better decision-making and policy development. Communication challenges are multifaceted, influenced not only by communication styles but also by complicating factors, such as model design (Wit et al. 2012), scientists' perception of the source of the uncertainty (Quigley et al. 2019), and prioritisation of these sources (Wit et al. 2012). Additionally, decision-makers' priorities, understanding of scientific concepts, and familiarity with uncertainty language impact how uncertainty is interpreted (Constable et al. 2022; Budescu et al. 2012; Wein et al. 2016). Establishing a shared understanding between scientists and decision-makers lays the foundation for effective collaboration, ensuring that both groups recognise each other's perspectives and roles (Steel et al. 2009b). Hence, this study examines the interactions between scientists and decision-makers, with a particular focus on the challenges and opportunities associated with communicating uncertainty. To ensure consistency in the research approach, interviews were conducted within the context of DRM. Drawing on interviews and literature, we identify key factors contributing to miscommunication and propose pathways to improve the communication of uncertainties of scientific models.

2 Research method

This research adheres to a constructivist epistemology (Goodrick and Rogers 2015; Creswell et al. 2007), which allowed us to gain deeper insights into understanding participants' perceptions. A qualitative research approach was adopted to examine how participants assign meaning to the research topic, considering that qualitative methods are well suited for capturing rich, context-specific insights (Creswell 2014). This section is divided into two subsections: Data Collection (including interviews with decision-makers and Scientists) and Data Analysis.

2.1 Data collection

This research employed semi-structured qualitative interviews for data collection, which allowed flexibility and depth in exploring participants' perspectives (Adams 2015). Participants were selected using snowball sampling to ensure relevant professional experience with natural hazard modelling and decision-making. Two groups were targeted:

- Scientists with expertise in developing or using hazard, risk, or climate models, primarily from government-funded research institutes, Universities, and Private research consultancies in New Zealand.
- Decision-makers involved in emergency management decision-making within central and regional government, local authorities, and related agencies.

Semi-structured interviews were chosen because they provide a structured framework whilst still allowing for open-ended responses, which is particularly useful for exploring complex topics, such as uncertainty communication, as in this research. This approach allowed us to guide the discussion whilst still capturing the nuanced perspectives of participants, making it particularly well suited for investigating areas where existing knowledge is limited or contested (Mogashoa 2014). Semi-structured interviews were also selected over other methods, such as surveys or focus groups, because they enable a deeper exploration of individual experiences and perceptions (Adams 2015), which are crucial for comprehending the intricacies of uncertainty communication.

2.1.1 Interviews with decision-makers

The first participant group in this study consisted of individuals with experience in decision-making for DRM for local and national government offices in Aotearoa, New Zealand. This group consisted of 15 participants; 13 interviews were conducted in person, whilst the remaining two were conducted via videoconferencing. These semi-structured qualitative interviews were conducted between June 1, 2021 and August 15, 2021, under a University human ethics notification classified as 'low risk'.

2.1.2 Interviews with scientists

The second group comprised scientists specialising in various aspects of DRM, including volcanic, earthquake, landslide, flood, and climate modelling. Selected through snowball sampling, they were chosen for their expertise in scientific modelling and their contribution to DRM decision-making processes. Interviews were conducted between May 26, 2022 and August 11, 2022, under a University human ethics notification classified as "low risk". In total, 17 semi-structured qualitative interviews were conducted, each averaging an hour, with more than 17 h of interview data used to analyse these research findings.

2.2 Data analysis

The data analysis process began with an initial review of the respective groups' interview data, including interview transcripts and notes taken during the interviews, to identify recurring patterns and concepts that informed the coding. The coding process involved coding sections of the transcript using NVivo software. This was followed by the identification of sub-themes through reflective thematic analysis, employing an iterative coding process with multiple cycles of refinement (Braun and Clarke 2019). These sub-themes were subsequently grouped into broader themes, which captured the nuanced insights derived from the data. An example of the code, sub-theme, and theme is provided in Fig. 1. This paper compares the themes and sub-themes identified and presented in Table 1. The comparison was guided by the research objective: to understand the dynamics between these two groups, with a particular focus on the barriers and opportunities in uncertainty communication. The comparison was conducted iteratively to ensure rigour in the analysis. The patterns of agreement or divergence were further scrutinised by returning to the raw data and examining the context of specific sub-themes. Reflective thematic analysis (Braun and Clarke 2019) was applied throughout the process to explore how the identified themes related to the broader research gap of uncertainty communication. The results of this comparative analysis were then used to draw insights into the interdependencies and miscommunications between scientists and decision-makers, providing a foundation for recommendations to improve uncertainty communication in DRM contexts.

Figure 1 presents a flowchart illustrating the analytical progression from code to sub-themes and themes. Highlighting these linkages is essential for conveying how the themes collectively contribute to this research's overarching narrative and insights. This diagrammatic representation illustrates how themes are interconnected through their sub-themes and associated codes. Themes represent broad categories that capture critical aspects of the data, whilst sub-themes are more specific elements within each theme.

3 Results: divergence and convergence

The relationship between scientists and decision-makers is shaped by deeper patterns of meaning that emerge through the analysis of interview data. These patterns are organised into themes and sub-themes, as summarised in Table 1. These themes and sub-themes were derived using the seven-step reflective thematic analysis process outlined by Braun et al. (2019). This comparison is crucial for revealing the nuances of uncertainty communication within the decision-making process for DRM. In doing so, the results section sets a foundation for understanding the distinctive perspectives held by each group, offering insight into the nuances of their interactions and communication practices.

This section identifies the differences and similarities between scientists' and decision-makers' themes, highlights the priorities of the two groups, and thus identifies areas leading to potential miscommunication of uncertainty, which are discussed in this section. The key diverging areas are as follows: (1) the perception of challenges, (2) communication approaches, (3) expectations and responsibilities, and (4) embracing uncertainties. In contrast, the converging areas are as follows: 1)

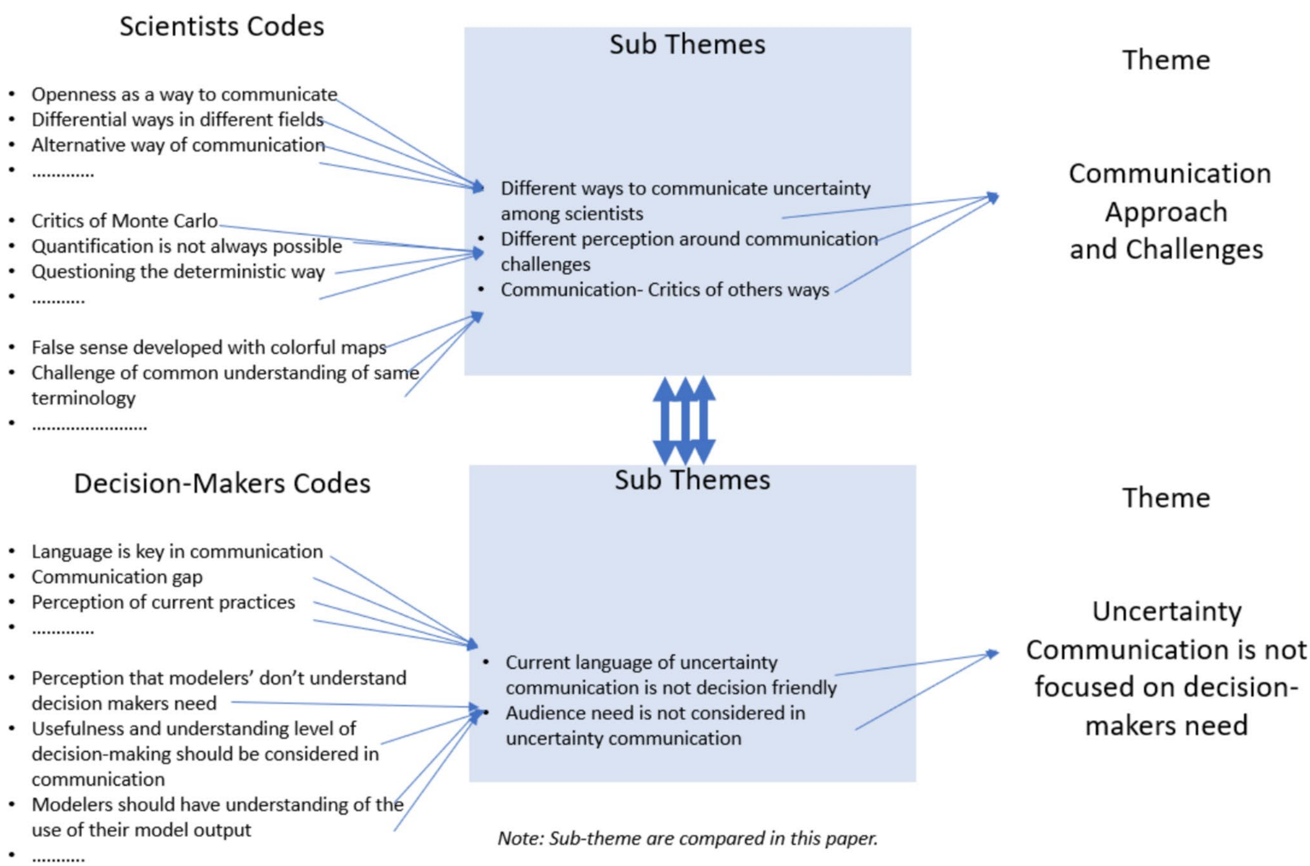

Fig. 1 An example of codes, sub-themes, and themes

the importance of uncertainty communication, (2) the acknowledgement of data, and (3) the collaboration of effective uncertainty communication.

3.1 Diverging areas

3.1.1 Perceptions of challenges due to uncertainty

Scientists view uncertainty challenges as stemming from the complexity of the data or models. They are focused on understanding the underlying dynamics, parameters, and assumptions of these models, thereby reducing the uncertainties associated with them and communicating the results to decision-makers. In comparison, decision-makers sought actionable insights from scientific models that could guide strategic planning, risk management, and policy formulation, amongst other decision-making activities. Decision-makers want to understand whether the uncertainty communicated to them would be helpful in their different decision-making activities. This difference has influenced how each group prioritises and addresses uncertainty. The following statements show where the focus of scientists and decision-makers lies regarding challenges around uncertainty:

"Are they in the same datum?….. Again, from the flooding side of things, you've got the river. You've got to have a river bathymetry, where some rivers might have cross-sections only. So you can use them to build up a bathymetry, but obviously, there's a lot of uncertainty between the cross-sections. …we're beginning to get things like a little unmanned drone…We still have sonar, or you've got cross-sections. You have to connect it in with the LIDAR, the topography. There are a lot of little details to get right to bring them in". —C04 Scientist

"It is almost like what are the short-term practical implications of uncertainty on their models, what does it mean, rather than just expressing it as a level of uncertainty. What does that actually mean? If they can consider that in that context, I suppose that would be helpful, rather than assuming any level of technical expertise on the part of the decision-makers". —D13 Decision-maker

In the first statement, scientists highlight the challenges of integrating diverse data sources, such as river bathymetry, sonar, and LiDAR, whilst addressing data gaps and compatibility uncertainties. In contrast, the second statement from

Table 1 Themes and Sub-themes from scientists and decision-makers' interview data

Scientists		Decision-makers	
Theme	Sub-theme	Themes	Sub-themes
Communication Approach and Challenges	Sub-theme	Uncertainty is a characteristic feature of scientific modelling	Understanding data sources and quality is important in modelling
	Different ways to communicate uncertainty amongst scientists		Understanding of the limitations of the scientific model
	Understand the differential needs of different users	Uncertainty communication is not focused on decision-makers' needs	The current language of uncertainty communication is not decision-friendly
	Different perceptions around communication challenges		Audience need is not considered in uncertainty communication
Model development and Characterisation	Communication-critics of other ways	Uncertainty is one aspect of the complex nature of DRM decision-making	Decision-making complexity and uncertainty are intertwined
	Data is a key factor of uncertainty		Uncertainty needs to be considered within the context of decision-making priorities
	Model design limitations as a key factor of uncertainty		Uncertainty requirement varies along the DRM cycle
Accountability and Opinion about other Experts	Model characteristics are an important aspect of uncertainty	Seeking certainty in uncertainty communication	The context of modelling is an important attribute of uncertainty in decision-making
	Different perceptions regarding the source of uncertainty		Reference to the Past serves well in decision-making
	What do other expects from them		Conservative decision pathways are used to avoid uncertainty
Collaboration	Perception towards others' responsibility		Scientists' experience and confidence are important
	Collaboration is a key to effective communication of uncertainty	Collaboration and trust as a way forward	Working relationships help communication
			Trust in modellers is a key for better integration of uncertainty in decision-making

decision-maker emphasises that scientists need to communicate the practical implications of uncertainty in models in a meaningful and accessible way without assuming the decision-makers' technical expertise.

The contrasting perspectives of scientists and decision-makers underscore their differing perceptions of the challenge that has shaped their engagement with uncertainty. It is clear that both groups are concerned about the uncertainty of a scientific model; however, they look from different vantage points—practical application for decision-makers versus methodological rigour for scientists. Scientists focus on data quality, model design, or assumptions as sources of uncertainty, whilst decision-makers view uncertainty as a broader risk management issue, applying this information to policy decisions.

3.1.2 Communication approaches

Scientists employ diverse strategies for communicating uncertainty, influenced by their unique methodologies and the inherent properties of their models. For example, scientists often frame uncertainties through probability density functions or use statistical distributions to represent uncertainty in data. One scientist explained:

> "Most of the uncertainties we describe are statistical, with distributions built from existing data. Our models reflect these uncertainties as we acknowledge what we know and what we don't". —A01 Scientist

This method showcases their commitment to transparent data representation, ensuring their uncertainty communication is grounded in empirical evidence. However, the intricacies of their models can complicate this communication. Models often rely on complex assumptions and intricate input–output relationships, which can be challenging for non-experts to simplify. Scientists are acutely aware of this, as demonstrated in the transcript below:

> "There are so many uncertainties in the whole chain of modelling that it becomes nearly impossible to figure out what they are at the end". - A04 Scientist

This sentiment highlights the challenge of making uncertainty comprehensible without oversimplifying or undermining the complexity of the scientific work, which is what most decision-makers were expecting.

Decision-makers expect clear, actionable insights, questioning the current ways scientists communicate uncertainty. Their frustration with the scientists not communicating uncertainty is reflected in the statement below:

> "I think sometimes you just got to be really clear that if you're talking to people, you need to be really clear with them. And you can say, we don't know what's going on, but our best guess is this is going to happen". —D11 Decision-maker

Scientists are hesitant to communicate uncertainty and choose to communicate what they perceive is important to decision-makers, as also highlighted by Fischhoff (2012). However, this might not align with decision-makers' expectations for clear communication. This is illustrated in the following quote:

> "Do we need to communicate everything? No way, We can't out of models. We've got such enormous complexity in our uncertainty that even communicating with scientists is quite challenging. So there's no way we would attempt to communicate that to any decision-maker". —A02 Scientist

The scientist's statement above can be considered understandable given the complexity they attempt to integrate into their model. However, this approach may result in miscommunication, potentially leading decision-makers to perceive scientists as lacking transparency. This paradox becomes particularly apparent when scientists employ probabilistic language in their communication, causing significant distress amongst decision-makers due to the complexity of the scientists' methods of communication. This is evident in the decision-maker's following statement:

> "In 2011, when two straight earthquakes hit us. They invited scientists. I can't even think of what .... said… 'So there's a 40% chance that this will recur or this is a once-in-40-year event'. So what does that mean to me ……… to get wrapped up in the mathematics and the probabilities and doesn't mean correct to the general public……unless you've got an advanced bloody mathematics degree, it just doesn't mean anything to you". —D09 Decision-maker

Our research also highlights that when such information reaches decision-makers, it leads to misunderstandings and raises doubts about its relevance to the decision-making processes. For instance,

> "They provided us with outputs from the model showing depth of water …………. Whether they had sufficient understanding of what the uncertainties were. Yes! they did say that the model didn't incorporate sea walls ……." —D13 Decision-maker

These observations underscore the importance of communicating uncertainty in a manner that clearly conveys its implications to the decision-maker and avoids technical jargon. This also highlights the importance for scientists to consider that most decision-makers are unfamiliar with complex statistical terminology.

3.1.3 Expectations and responsibilities

Scientists and decision-makers have different expectations of each other. Decision-makers often expect scientists to simplify complex uncertainties into clear recommendations, whilst scientists expect decision-makers to consider the inherent limitations and uncertainties in scientific data when making decisions. In addition, scientists tend to prioritise certain methods of uncertainty communication based on their training (Dhungana et al. 2025). Decision-makers have different expectations from scientists, as illustrated in the statement below. Decision-makers expect scientists to communicate in a clear and straightforward manner.

> "Scientists have got to be able to explain their science in their advice, in a straightforward way that allows controllers to make decisions. And sometimes scientists don't understand why they've been asked for information. And controllers don't understand the limitations on what they've been given". —D11 Decision-maker

In addition to that, decision-makers highlight that it is essential to understand the context in which a particular model is being used to communicate uncertainties effectively (Windschitl and Weber 1999; Bilgin and Brenner 2013), as illustrated below:

> "Uncertainty needn't be a very scientific complicated (+ or -) point or percentage. Having almost a number around uncertainty wouldn't have been so meaningful or necessarily useful. But things like saying what is in the model or what the model is based on, Older DEM is based, but we have better LIDAR, all those sorts of things. Those sorts of factors, I think, would be really useful". —D13 Decision-maker

Decision-makers also seek explanations and methodologies to understand uncertainty. As stated below,

> "We need to know, when there were three choices, they selected one; why did they select that one? It could be that this weather event is modelling what happened in 2015. So they've selected this model because this is the 2015 model". —D05 Decision-maker

Hence, decision-makers criticise scientific communications that frequently neglect the audience and do not consider the practical applications of decision-making. This divergence underscores the need for communication strategies that effectively reconcile the complexity of uncertainty with the pragmatic needs of decision-making, whilst also presenting it in a comprehensible manner for both scientists and decision-makers. Such strategies are essential for bridging the gap between scientific uncertainty and the actionable insights required in real-world contexts, ensuring that uncertainty is communicated not only accurately but also in a manner that facilitates informed and timely decisions.

3.1.4 Embracing uncertainty or seeking certainty: the disciplinary differences

Decision-makers strongly prefer seeking certainty in their decision-making processes, which contrasts with scientists' focus on understanding and refining models, accepting uncertainty in scientific models as a fundamental part of this process (Dhungana et al. 2025). The differing preferences and communication behaviours between decision-makers and scientists are deeply rooted in their roles and objectives, as evidenced by the reasoning they share.

This divergence stems from the different nature of their roles. Scientists adopt an uncertainty reduction approach (Pinelli et al. 2020), emphasising the complex sources of uncertainty and using various techniques available for addressing uncertainty, such as sensitivity analysis (Refsgaard et al. 2007). They engage with the intricacies of uncertainty, exploring its diverse sources—whether due to inherent limitations in knowledge, variability in data, or contextual factors (Spiegelhalter and Riesch 2011). As a scientist noted,

> "The data and getting the data right are a big part. Also, what are you actually modelling? There are big questions in terms of how you're forcing this model. It very much depends on what you're doing". —C04 Scientist

This reflects the inherent challenges of data reliability. This mindset prompts scientists to consider embracing uncertainty. Meanwhile, decision-makers prioritise certainty in the information provided to guide their choices during uncertain situations. Decision-makers prioritise seeking certainty amidst the uncertainties presented by scientific models. For them, *'certainty'* translates to clear, actionable information that can support decisions under risk. One decision-maker remarked,

> "I really need you to tell me 40%, 80%. He told me a number, and once they got it in their head that I needed that kind of certainty". —D11 Decision-maker

Similarly, the other decision-makers emphasise,

> "Sense making is the key to good decision-making". —D09 Decision-maker

This showcases their need to distil complex information into practical strategies. Scientists also corroborate this attitude of decision-makers:

> "When you start talking, we definitely want to talk about uncertainty. We want people to understand it's

> uncertain, here's our confidence. But it quickly goes the other way, where people start saying, we just don't believe anything because you don't know what you're doing. Because there's too much uncertainty". —A02 Scientist

The above statement from scientists indicates that scientists are expected to provide certainty, despite the considerable uncertainty in modelling.

Furthermore, decision-makers highlight their reliance on historical references and past experiences as essential tools for risk mitigation and suggest they seek certainty through their experiences for their decision-making, as stated below:

> "If we're talking about a flood scenario, a model that will give us a sort of best-case scenario and a worst-case scenario. We use a mixture of our experience, local expertise and their understanding of what they've seen, aligned with that model. And then we tried to make the most appropriate decision considering all those factors". —D07 Decision-maker

This statement reflects a pragmatic approach to uncertainty communication. Decision-makers are not solely reliant on the outputs of scientific models; instead, they use these outputs as one component in a broader matrix of decision-making considerations. However, this conflicts with scientists' emphasis on the iterative and uncertain nature of model development (Dhungana et al. 2025). Scientists maintain a nuanced understanding of the origins and implications of uncertainty in their work, as reflected in their concerns. As one scientist stated,

> "The problem with all of this stuff that we do in hazards, and whatever, is that we never know if the answer coming out is correct". —A01 Scientist

This emphasises the inherent challenges they face. They also noted:

> "The data that we use, it's reanalysis data. So it's not actually real data. It is data that they have built from assuming this huge world model". —A01 Scientist

This points to the complexities involved in data interpretation. In contrast, decision-makers prioritise the need for clear and reliable information, viewing the context of modelling as a critical aspect of managing uncertainty. They rely on historical references and past experiences, further illustrating a preference for conservative pathways to mitigate uncertainty.

This comparison reveals a fundamental difference in focus: scientists concentrate on technical precision and model reliability, whilst decision-makers balance multiple factors in a broader context. Although scientists highlight data as a critical contributor to uncertainty, decision-makers emphasise practical strategies and the utility of past experiences. This divergence underscores both groups' distinct roles and concerns, highlighting how the scientists' focus on understanding uncertainty contrasts with the decision-makers' quest for clarity and certainty in informing and assisting their decision-making processes.

3.2 Converging areas

Several converging concepts underpin effective communication within the realm of modelling and decision-making, which are discussed in this section.

3.2.1 Importance of uncertainty communication

Both groups recognise the need for communication of uncertainty. Whilst their methods may differ, there is an understanding that clear, transparent communication is essential for informed decision-making, which aligns with the findings. Spiegelhalter and Riesch (2011) from that highlight that acknowledging and transparently communicating uncertainty is not a sign of weakness but rather a crucial aspect of responsible scientific practice. The following statements from both the scientists and the decision-makers clearly support this view:

> "Honestly, there's a need for uncertainty '101'. Something that actually does really effectively outline the limitations of models. The limitations of models with respect to policy and decision-making". —C05 Scientist
> "So there needs to be some practical approach. But I think it needs to be provided in way that is useful, and decision-makers understand". —D13 Decision-maker

These statements emphasise the importance of acknowledging the limitations of models, which are often discussed in terms of uncertainty in policy and decision-making. Scientists emphasise the need to teach the fundamentals of uncertainty in scientific models, where decision-makers stress the need for practical approaches that clearly and effectively present uncertainty, ensuring it is understandable and valuable for informed decisions. Both suggest the need and significance of communicating uncertainty.

Another converging idea regarding the importance of communicating uncertainty revolves around the use of scenario-based communication, which is also highlighted by McMahon et al. (2015) in IPCC scenario graphs. Recognising the complexity of decision-making environments, scenario-based communication offers a structured approach to conveying information. A plausible scenario and its potential outcomes help decision-makers more intuitively grasp the implications of various courses of action (Lawrence et al. 2019). They believe that this approach facilitates a shared understanding amongst stakeholders, enabling informed decision-making processes that account for the system's uncertainties and complexities.

> "Giving you the tools to actually go off and find some other material will actually help develop your thinking within the scenarios". —D07 Decision-maker

Similarly, Scientists also understand the importance of scenarios, as suggested in the following statement.

> "They like scenarios, things that they can look at, they don't like distributions. So, if you start trying to present anything as a probability distribution, good luck, because they won't understand". —B03 Scientist

3.2.2 Acknowledgement of data as a key part of understanding uncertainty

Data quality and limitations in model design have been previously recognised as significant sources of uncertainty (Budescu et al. 2012; Uusitalo et al. 2015). They were also recognised by both the scientists and decision-makers in our research, as discussed in the multiple quotes below:

> "What sort of data is appropriate to include and exclude. At what level…going down to really find micro data, or whether you're aggregating data up and using it at that level. And also, of course, …there are parameters that you don't have any data for, so you're actually having to make assumptions". —C01 Scientist
> It is really important to have good data. And understanding the inherent limitations on that data. It needs to be fit for purpose and available as and when you need it. —D08 Decision-maker

In the statements above, scientists and decision-makers have highlighted the importance of data quality and model design. Scientists emphasise the complexities of using data, whereas decision-makers, echoing this sentiment, stress the importance of having reliable, fit-for-purpose, readily available data, along with an awareness of its limitations. However, scientists delved deeper and highlighted the selection of appropriate input data for their model, whether at the micro-level or aggregated, and the necessity of making assumptions when data are lacking, thereby introducing uncertainty. Whilst this shared emphasis points to a common concern across both groups, it is important to recognise that the DRM context might have made their preference for actionable information over probabilistic or abstract representations. However, this shared understanding between scientists and decision-makers indeed emphasises the need for a collaborative approach to address data uncertainties, fostering more robust and effective decision-making processes. As also noted by Shome et al. (2018), data serve as the cornerstone of any model, meaning that the inherent uncertainty directly translates to uncertainty in the model's predictions. This relationship underscores the importance of ensuring high-quality data and being aware of its limitations.

3.2.3 Collaboration for effective uncertainty communication:

Although disparities emerged in different areas, as discussed earlier, which can result in prompting miscommunication, there are still areas of common ground that can be leveraged to enhance communication, such as collaboration between scientists and decision-makers. There was agreement between our decision-makers and the scientist groups that collaboration is crucial for effective communication of uncertainty. A specific example of collaboration between scientists and decision-makers, shared by both scientists and decision-makers, is AF8,[1] in the context of New Zealand's (NZ) South Island. The collaboration of scientists and decision-makers in AF8 suggested that collaboration not only facilitates joint problem-solving but also enhances the clarity, relevance, and transparency of information exchanged between parties, which enables the communication of complex areas, such as uncertainty.

Both scientists and decision-makers recognise that working together can improve the interpretation of scientific findings and their application in policy contexts, as suggested in the following transcript:

> "There's increased concern nowadays amongst scientists in terms of providing hazard or risk information. I think having relationships in place makes it a lot easier, probably to have the conversation around the hazard and risk". —D13 Decision-maker

> At the end of the day, communities and decision-makers in local government they're going to need to make decisions. So, we need to somehow build their capability as well to handle and deal with complex information, including the results of models. By involving them in or at least allowing them to look at and better understand how projections or scenarios or modelled results are produced, they can then build their own capability in terms of handling complex information, working with probabilities, communicating some of those results to key stakeholders and constituents, etc. —C05 Scientist

[1] https://af8.org.nz/ AF8 [Alpine Fault magnitude 8] is an award-winning programme of scientific modelling, coordinated response planning, and community engagement, designed to build resilience to the next Alpine Fault earthquake.

In both statements above, the need for collaboration is highlighted. Decision-makers highlight the importance of building solid relationships with scientists to understand uncertainties in scientific models better, and scientists underscore the need for collaboration so that decision-makers will be empowered to understand and handle complex information and modelling results to improve their decision-making capabilities, recognising that effective communication of uncertainties requires close cooperation between both parties.

Participants discussed trust as another important factor for effective collaboration. Cross and LaDue (2020) highlight that trust is critical for managing complex information and fostering shared understanding, especially when dealing with uncertain and often contentious data, which is also highlighted by both scientists and decision-makers in our research, see the following transcripts:

> "In terms of trust, it's more of a respect. There's probably not anyone that knows everything. So a lot of it's just trust in terms of who you work with". —C03 Scientist
> "My opinion is, it's wrong of us to need to know too much detail that's outside of our pay grade, so to speak, or outside of our area of knowledge, because we should be relying on the experts to relay it in a way that we can understand what the implications are, and how it's looking". —D05 Decision-maker

In the above, the scientist emphasises that trust is built on mutual respect and the expertise of colleagues, suggesting that collaboration relies on knowing who to rely upon. The decision-maker believes that it is inappropriate for them to delve too deeply into areas outside their knowledge, advocating for clear communication from scientists to help them understand the implications of decisions.

4 Discussion

Decision-making hinges on clear communication between scientists and decision-makers (Doyle and Paton 2018; Doyle and Johnston 2011; Horita et al. 2017; Quigley et al. 2019). This multifaceted process involves diverse stakeholders and considerations, making effective communication paramount (Smith et al. 2016). Building on earlier result sections, the analysis highlights key factors contributing to miscommunication and offers pathways to enhance mutual understanding, particularly in communicating model uncertainty. The divergent perspectives and communication strategies between the two groups (scientists and decision-makers) highlight why a shared framework for communicating uncertainties is so essential, as also suggested by several authors (Bevan 2022; Doyle et al. 2019).

Uncertainty in the scientific model must be actively addressed and communicated to decision-makers. Both groups of participants (scientists and decision-makers) recognise the importance of data used in models as a critical source of uncertainty. However, their approaches to addressing this challenge differ significantly due to the distinct contexts within which they operate.

Scientists engage with the complexities of uncertainty by exploring its diverse sources—whether these stem from limitations in knowledge, data variability, or contextual factors (Quigley et al. 2019; Walker et al. 2003). Their approach focuses on identifying, characterising, and communicating uncertainty, driven by their role in generating and interpreting data. In our research, the scientists' emphasis lies in ensuring methodological rigour and transparency, understanding the assumptions underlying models, and accurately representing the limitations of predictions (Winsberg 2012). This reflects their training, prioritising analytical and exploratory methods for understanding uncertainty and its implications. In contrast, decision-makers frame uncertainty regarding its practical utility and implications for decision-making processes (Coughlan de Perez et al. 2022; Smith et al. 2016). Their priority extends beyond understanding the nature of uncertainty to evaluating its impact on policies, resource allocation, and risk mitigation strategies (Patt 2009; Wardekker et al. 2008; Horita et al. 2017). Whilst scientists focus on the technical and methodological aspects of uncertainty, decision-makers prioritise its relevance and application in real-world contexts, highlighting the need for improved communication and collaboration between the two groups to bridge the gap and enhance the effectiveness of uncertainty communication in decision-making processes.

Further, effective communication hinges on a shared understanding of language and terminology (Schneider 2016). As discussed in the results, scientists often use specialised terms, and the use of this specialised language presents a significant barrier to effective communication of uncertainty (Kahan 2010; Lammers et al. 2024). For example, scientific terminology rooted in probabilistic language, such as 'sensitivity' and 'confidence interval', along with sophisticated tools like Monte Carlo simulations (Cunha et al. 2014) can be unfamiliar to decision-makers. Additionally, these terms and tools may carry different meanings or interpretations depending on the decision-makers' contexts and disciplines, further complicating communication.

Decision-makers also prefer probabilistic statements of uncertainty to be more helpful and clear (De Bruin et al. 2000; Ramos et al. 2013). Lack of clarity can lead to the misinterpretation of scientific uncertainty, as seen in the case of visualising hurricane track uncertainty using an uncertainty cone (Broad et al. 2007). We recommend that communicators present uncertainty information through visually engaging formats to enhance understanding, as highlighted by

Lucchesi, Kuhnert, and Wikle (2021), Krisper et al. (2019) and Lilburne et al. (2022). These visual displays should also be tested for their effectiveness in improving comprehension and supporting decision-making (Clive et al. 2023; Bostrom, Anselin, and Farris 2008). This recommendation arises partly from the ongoing debate over the use of probabilistic language in uncertainty communication. Both scientists and decision-makers in our study noted that probabilistic statements, often employed by scientists, can be perceived as a sign of indecisiveness or unreliability by decision-makers (De Bruin et al. 2000; Seidenfeld et al. 2012).

The communication barriers between scientists and decision-makers extend beyond linguistic differences. They also involve deeper issues, such as differing expectations and responsibilities (Doyle and Paton 2018). Both groups are concerned with effective communication, but their priorities differ. Scientists focus on methodological rigour, whilst decision-makers emphasise the practical application of information. Scientists view uncertainty as stemming from data quality, model design, and assumptions, whereas decision-makers consider uncertainty within the broader context of risk management (Quigley et al. 2019). Decision-makers rely on scientists to forecast future developments and provide insights into potential outcomes (Doyle & Paton 2018; Padilla et al. 2021a, b). They expect clear communication of the uncertainties associated with these predictions. However, decision-makers primarily seek certainty, often due to the practical need for firm decisions in high-stakes contexts. This expectation is driven by the nature of their roles, where actionable, concrete recommendations are prioritised. Conversely, scientists may be hesitant to disclose uncertainties, as their training and epistemological frameworks emphasise precision and objectivity. They often fear that acknowledging uncertainty could undermine their credibility, particularly in environments where definitive outcomes are valued over nuanced, probabilistic ones (Cross and LaDue 2020). These differences in expectations stem from divergent operating practices: decision-makers typically operate under time constraints, whilst scientists are accustomed to working with complex, evolving models that inherently involve uncertainty.

Both groups agree that scientific models are vital, although they are not always able to replicate reality accurately, and both the scientists and decision-makers advocate towards good science to happen, as also suggested by Hartman et al. (2025). Yet the current communication methods are heavily shaped by scientists' training, with scientists sometimes reluctant to communicate uncertainties, fearing that this could weaken their authority. Scientists, whilst recognising the versatility of their methods, acknowledge that decision-makers who lack statistical knowledge may not fully grasp technical terminology, leading to ambiguity and misinterpretation (M. Maier et al. 2016). This results in dissatisfaction amongst decision-makers, who often find current uncertainty communication methods unhelpful for decision-making. Both groups agree that existing methods are not sufficiently user-focused, as identified by (Kox et al. 2018; Frick and Hegg 2011), with scientists specifically highlighting the lack of effective communication tools as a key challenge.

Interestingly, both groups recognise the limitations of existing communication strategies. Whilst scientists hesitate to disclose uncertainties, fearing reputational risks, decision-makers seek more precise communication of uncertainties without overwhelming technical details. This tension reveals underlying differences in their decision-making processes. Scientists often approach decisions analytically, focussing on model precision and validation, whereas decision-makers may follow rule-based or scenario-driven frameworks to address pressing needs (Doyle et al. 2019). The divergent perspectives and communication strategies between these groups underscore the importance of a shared framework for communicating uncertainties.

To mitigate uncertainty and communication challenges, early engagement and sustained collaboration are paramount. The AF8 initiative in New Zealand exemplifies how trust-based collaborative efforts can enhance preparedness and mutual understanding between scientists and decision-makers (Orchiston et al. 2018). We suggest that such initiatives can be potential pathways for effective communication of uncertainty. By fostering this collaboration, scientists and decision-makers can co-create communication tools that balance scientific integrity with practical usability, ultimately supporting robust and adaptive DRM strategies. Whilst previous literature extensively discusses the communication barriers between scientists and decision-makers, particularly concerning the presentation and interpretation of probabilistic information (Durbach and Stewart 2019; Ramos et al. 2013; Handmer and Proudley 2007; Budescu and Wallsten 1995), our findings contribute new insights by pinpointing the contextual roots and nuanced ways these misunderstandings manifest in the field of disaster risk management (DRM). Specifically, whilst it is well documented that decision-makers may interpret probabilistic statements as indecisiveness (Seidenfeld et al. 2012; De Bruin et al. 2000; Handmer and Proudley 2007; Doyle et al. 2014; Ramos et al. 2013), our research delves deeper into the underlying dynamics, such as the specific ways decision-makers seek actionable certainty and how this expectation conflicts with probabilistic ways of communicating uncertainty, which in itself cannot provide any certainty to decision-makers. Hence, a unique contribution of our work lies in identifying the implications of this disconnect in real-world DRM settings, where high stakes and time-sensitive decisions exacerbate communication challenges. For example, we found that decision-makers' dissatisfaction often stems from the use of probabilistic language and a lack of user-focused communication tools and visual aids tailored to their specific needs. This gap is less commonly addressed in existing studies, and this finding underscores the need for a greater emphasis on co-creating accessible strategies for communicating uncertainty.

Our research contributes to the discourse by examining the tensions arising from the professional training and theoretical orientations of scientists versus those of decision-makers. Whilst prior work notes the existence of differing frameworks (Quigley et al. 2019), this research highlights specific instances where these divergences lead to misunderstandings about model limitations, forecasting, and credibility concerns. Moreover, the role of trust-building through initiatives like New Zealand's AF8 collaboration showcases practical pathways to bridging communication gaps, emphasising that this type of collaborative model will facilitate effective communication of uncertainty.

Furthermore, scientists and decision-makers criticise each other: scientists argue that decision-makers oversimplify uncertainty, whilst decision-makers feel that scientists complicate it without adequately addressing practical implications. Such collaboration would bridge the gap, especially for technical vocabulary needed for fostering common understanding, where (Spiegelhalter 2017; Spiegelhalter and Riesch 2011; Van Der Bles et al. 2020) have identified these problems concerning the technical vocabulary of uncertainty. Hence, our research extends beyond affirming known challenges to providing practical, context-driven insights into why they persist and how targeted communication strategies can address them.

Creating knowledge together through intensive face-to-face interactions is crucial for understanding limitations and the needs of practitioners, ultimately fostering mutual understanding and effective problem-solving (Barton et al. 2020). This mutual recognition underscores the importance of collaboration between the two groups in bridging the gap in uncertainty communication. Hartman et al. (2025) also highlighted the value of collaboration at the start of the model development in their research in application-driven artificial intelligence (AI). Similarly, the significance of collaboration in improving uncertainty communication aligns with the recent development of the DAP (Dynamic Adaptation Pathways) approach, which advocates for scenario-based communication of uncertainty (Lawrence et al. 2019). The DAP approach is particularly well suited for fostering collaboration, as it involves creating flexible, adaptive pathways that account for different future scenarios. By explicitly integrating uncertainty into decision-making processes, DAP encourages stakeholders to explore a range of potential outcomes and their associated risk (Kwakkel et al. 2013; Haasnoot et al. 2013; Lawrence et al. 2019).

5 Limitations and future research

This study primarily focused on participants based in New Zealand who work in DRM. The research design is tailored to this specific domain, which could influence the findings. For instance, the participants' experience levels were not extensively examined, which may affect their approaches to communicating uncertainty and their perspectives or preferences regarding how uncertainty is conveyed or received. Whilst there was no significant divergence in opinions amongst the participants, this homogeneity may not provide insight into the perspectives of individuals working in other domains beyond DRM. Thus, future research could expand the scope by including participants from diverse sectors, which would provide a broader understanding of how uncertainty communication is approached across various fields. Additionally, examining the role of experience level, organisational context, and cross-disciplinary collaboration could further enrich insights into how different professional backgrounds influence the interpretation and communication of uncertainty.

6 Conclusion

The contrasting priorities of scientists and decision-makers regarding uncertainty highlight a critical need for tailored communication strategies and collaborative approaches. Whilst their perspectives diverge in many respects, the shared goal of improving uncertainty communication for better decision-making in DRM provides a foundation for convergence. Recognising and leveraging these commonalities can enable more effective communication, foster trust, and ultimately enhance the application of scientific models in decision-making contexts related to DRM.

We suggest that addressing the communication gap between scientists and decision-makers requires targeted efforts in three key areas. First, capacity-building initiatives are essential for enhancing decision-makers' understanding of scientific uncertainty whilst equipping scientists with practical communication skills tailored to non-technical audiences. Second, the collaborative participation of decision-makers and scientists, starting right from the model development stage, ensures a better understanding of uncertainty and facilitates effective communication between the two groups. This collaboration helps break down the silos between scientific modelling and decision-making, fostering the development of models that are both scientifically rigorous and tailored to meet the needs of decision-makers. Finally, developing enhanced visualisation tools offers an opportunity to present uncertainty in a user-friendly manner, facilitating the interpretation and application of scientific data in decision-making processes. These strategies can foster a more integrated approach to managing uncertainty in complex decision-making contexts.

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Declarations

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