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Navigating scientific modelling and uncertainty: Insights from hazard, risk, and impact scientists in disaster risk management (DRM)

Annal Dhungana [a,*], Emma Hudson Doyle [a], Garry McDonald [b], Raj Prasanna [a]

[a] Joint Centre for Disaster Research, Wellington Campus, Massey University, P.O. Box 756, Wellington, New Zealand
[b] Market Economics, PO Box 331297, Takapuna, 0740, Auckland, New Zealand

A B S T R A C T

Scientific models have long been used as an important tool in assisting in decision-making in Disaster Risk Management (DRM). However, it is commonly understood that uncertainty in these models significantly influences the integration of model outputs into decision-making processes, presenting a challenge for effective uncertainty communication. This paper explores how scientists in DRM approach modelling and uncertainty.

We conducted seventeen in-depth qualitative interviews in Aotearoa, New Zealand, with scientists working on DRM. We provided an overview of the varied approaches and key factors influencing their processes for model characterisation and communicating uncertainties. We used Reflective Thematic Analysis to construct key themes, including (a) model development and characterisation, (b) accountability and opinion, (c) communication approach and challenges, and (d) collaboration for effective uncertainty communication.

We found that different DRM scientists have different disciplinary and experiential training, experience, and interaction with decision-makers. These factors greatly influence their choices regarding scientific modelling and communication of uncertainty. The lack of a generally accepted guideline for a best practice approach to uncertainty communication is a key barrier to successfully incorporating uncertainties into DRM decision-making. We suggest that a better collaboration between scientists and decision-makers throughout the lifecycle of the model development process is a way forward for effective communication of uncertainty in DRM decision-making.

1. Introduction

Scientific models are essential tools in science, including Disaster Risk Management (DRM). These models help us understand complex natural processes and, hence, are crucial in shaping our subjective understanding and interpretation of reality [1]. However, it is critical to recognise and understand that uncertainties are ubiquitous with these models [2,3], from inputs/data choices, model algorithm choices, and assumptions made to modelling and model processing, as well as when generating estimates and projections [4,5]. All these manifestations of uncertainty heavily guide scientists while they develop scientific models to support the understanding of the complex reality surrounding DRM decision-making.

The complexity around uncertainties can be considered understandable, considering the use of different types of models and modelling to assist DRM decision-making [6–9]. However, these differences also make it difficult for decision-makers to consider uncertainties in their decision-making processes [10]. Scientists use various techniques to express these uncertainties to improve the models' usefulness [6,11,12]. However, comprehensive studies examining how different scientists are involved in uncertainty communication of scientific models are notably lacking [5]. It is crucial to investigate this aspect because scientists come from multiple

* Corresponding author.
E-mail addresses: annal.dhungana.1@uni.massey.ac.nz (A. Dhungana), e.e.hudson-doyle@massey.ac.nz (E. Hudson Doyle), garry@me.co.nz (G. McDonald), r.prasanna@massey.ac.nz (R. Prasanna).

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disciplines [13], and their disciplinary knowledge can influence their interpretation and communication of uncertainty. The lack of research in this area has meant that guidance on effective communication of uncertainty to decision-makers is yet to be fully developed. Hence, this paper investigates the views of scientists working in DRM and provides an overview of the major factors influencing the modelling and communication of the uncertainties associated with the scientific models.

When it comes to DRM decision-making, there are multiple actors involved as decision-makers [14,15]; therefore, to streamline the discussion, we want to highlight that decision-makers in this paper's context primarily refer to the advisors and analysts who utilise model outputs to inform strategies and actions within DRM, along with advising the elected decision-makers. The scope of this research paper is also limited to the uncertainties of scientific models and excludes discussion on "deep uncertainties". Such deep uncertainties require more detailed investigation and have been considered to be beyond the scope of this research at this time. However, we recommend it be included in future research that considers how such a complex concept can be conveyed through a visualisation tool, and we direct readers to Refs. [16–18] for further discussion of deep uncertainty communication".

This paper initially explores the different scientific models and modelling in DRM (Section 1.1) and then explores the uncertainties in these scientific models and uncertainty communication (Section 1.2). These two segments highlight the extant literature around the conceptualisation of models and strategies adopted for communicating uncertainty. Building upon these foundational concepts, we investigate associated methodological approaches (Section 2). Section 3 explains the diversity observed among research participants (scientists), and Section 4 discusses the rationale behind this diversity and outlines recommendations for future research.

1.1. Scientific models for DRM decision-making

Every scientific model built is a mental construct that helps scientific reasoning [1]. These models support decision-making in complex real-world situations [19], providing the knowledge base for simplifying reality [20]. However, reality is independent of the model descriptions. Despite attempts to incorporate intricacies of reality in models, models are always simplifications of reality and are inherently imperfect [21]. However, models can help us understand reality to some extent [22] and, thus, assist in decision-making. Frigg and Hartmann (2021) nicely summarised the scientific model as a simplified representation of a system, process, or phenomenon used to make projections, simulate the system's behaviour, or understand its underlying mechanisms [22]. Wherever "model" is used, it should be understood as representing scientific models developed and used by scientists, as per the definition of Friggs and Hartmann (2021). As this research is limited to the DRM, these scientific models discussed are also used in decision-making in the DRM context.

In DRM, models help decision-making in different hazard and disaster situations, allowing more informed decisions before the event unfolds [23–26]. The most common usage of models is based on their explanatory and projection power [27], ranging from explaining hazard and risk scenarios [28] to more novel applications, such as early warning for different hazards and disasters [29]. Along with the identification of hazards and risks, models are also used to understand the societal impact of such hazards and disaster situations [14,30,31], where they combine basic principles of characterisation of hazards for some geographical regions, identification of the risks the hazards carry, and identifying the social factors that are susceptible to impacts over time. Models influence our understanding, perspectives, and actions and help us understand the trends, which is helpful in DRM decision-making [14,31–34].

It has been observed that a diverse range of professionals, spanning from hazard scientists to risk scientists to engineers [35], natural scientists to climate scientists [36] to socio-economic experts to impact scientists [34], dedicate their scientific careers in developing scientific models. However, the motivation for model development varies among individual scientists, driven by their own disciplinary focus such as Earthquake Scientists [32] focus on seismic hazards, Volcanic Scientists [37] focus on volcanic eruptions, and Social and Economic Scientists [38] focus on socioeconomic impact, all of which are contributing towards the overall goal of DRM planning.

Models can be categorised in several ways [22]. However, when discussing uncertainty in these models, it has been observed that the differences exist depending on whether a deterministic or probabilistic model is being considered [39,40]. On one hand, deterministic models typically consider a single scenario model and usually quantify the impact of a hazard, disaster event, or a collection of events but do not attempt to describe the full range of events that might happen [41]. On the other hand, probabilistic models bring together many events and associated estimates of the probability of occurrence of each event over a time period. Probabilistic models have been preferred over deterministic modelling in DRM in recent decades [42]. However, probabilistic models also face challenges in practical application, particularly when modelling rare, extreme events [43,44]. For example, earthquakes [45] are so infrequent that the available data for estimating their probabilities is often limited. As a result, scientists face significant uncertainty in predicting their likelihood, and the conventional methods of probability estimation may not provide reliable forecasts. Hence, probabilistic models also face challenges in practical application due to the extreme nature of the events being modelled, which are so rare that probabilities are difficult to estimate [46]. Independent of whether these models are deterministic or probabilistic, a key aim is to provide information about hazards and their risk and impact to aid in disaster planning decision-making. Hence, Models are tools used in DRM decision-making, but with such models come uncertainties, and communicating uncertainty adds another layer of complexity for scientists and decision-makers alike, where the uncertainty of a model is sought to be discussed from the outset of model development [47].

1.2. Model Uncertainty and Uncertainty Communication

Uncertainty is inherent in the scientific model and emerges on multiple fronts through the intricacies of inputs [3,4,48,49]. The context in which models are applied, the modelling processes, and the model dynamics play a significant role in how uncertainty is understood, acknowledged [50,51], and communicated by scientists [3]. In defining uncertainties, there is a practice of differentiating between lack of knowledge (epistemic uncertainty) and randomness of the system (aleatory uncertainty) [52,53]. These approaches support statistical thinking, providing a structured way to quantify, interpret, and communicate uncertainty [48,49]. However, some critics argue that it is challenging to differentiate between epistemic and aleatory uncertainty when the line between natural variability and lack of knowledge is vague [54,55]. While the discussion on uncertainty lacks conceptual clarity and consistency [56], its importance in decision-making is not doubted, where diverse scientists have highlighted that incorporating uncertainty in scientific advice helps to support complex decision-making surrounding risks [4,57].

Uncertainty, when viewed as a mathematical artefact, is solely aimed at assessing the effects of known uncertain variables for which probability distributions can be populated [9,58]. Uncertainty in models may also be analysed through a sensitivity analysis - where particular variables in a model are known to be uncertain, but no distribution exists [59,60]. A common practice towards treating uncertainty among scientists is focusing on "uncertainty reduction", particularly for those working in hazard identification and risk characterisation [57,61]. In the models used in hazard identification and risk characterisation, probabilistic estimates assume uncertainty can be treated as a random variable and can be quantified. Gustafson (2019) has termed these quantified uncertainties as 'technical uncertainty', where a probability distribution is often used to express uncertainty in a modelling exercise [11] These uncertainty reduction techniques require effort to minimise or eliminate uncertainties in scientific measurements, predictions, or models [62]. While striving for increased precision and accuracy is a legitimate goal, overemphasising uncertainty reduction can lead to a misleading sense of certainty [63]. When there is a complex situation like a disaster or emergency, uncertainty quantification, expressed in probabilistic terms, might be confusing [64]. Despite most of the work on uncertainty and uncertainty communication focusing on quantification, it's duly acknowledged that this issue can't be dealt with only by quantification [65,66].

When focused on the robustness of the model and reducing uncertainty, scientists argue this makes their estimates more beneficial for the users of their model [67]. Uncertainty in a modelling exercise is also discussed as a characteristic of events that are not statistically predicted and a way in which the future can be imagined or predicted [68]. This is standard practice among scientists working to identify impacts regarding loss. Scientists also use scenarios to explore input values, assumptions, and limitations, helping to understand the range of possible outcomes and associated uncertainties [69]. Expert judgment is also employed to help identify and mitigate uncertainties, especially with limited data sources [70]. Hence, scientists cover various uncertainty types, origins, and manifestations, highlighting the complexity of comprehending uncertainty.

In our research, we recognise the critical role of scientific modelling and its associated uncertainties in informing DRM decision-making processes in New Zealand. We explore 1. the critical modelling attributes leading to uncertainties and 2. understanding the tools and techniques used by the scientists in communicating uncertainties. Through this research, we aimed to contribute to the improved understanding of barriers and enablers associated with uncertainty communication among scientists and identify pathways for better integration of uncertainties in DRM decision-making.

2. Methodology

2.1. Data collection approach

We employ a qualitative interview method for this study because this method is rooted in the idea of listening to the views of diverse participants [71] A qualitative semi-structured interview technique was selected to enable a deeper exploration of diverse perspectives that would not be possible with quantitative and other techniques [71]. The semi-structured design also allows further lines of enquiry in the interview to explore aspects of participants' views further as needed. This technique was necessary due to the complex, varied, and nuanced nature of individuals' understanding and communication of uncertainty [72]. Adopting a qualitative interview approach provides opportunities for diverse perspectives to be explored. Cresswell (2007) further suggests that qualitative interviews use the flexible framework of the study questions with possible changes in questions with different interviewees as per their mental framework rather than a structured questionnaire as used in mixed methods research. A quantitative survey, or structured qualitative interview, is likely to miss essential lines of enquiry in the discussion with scientists [73], and may not allow deeper patterns of meaning to be drawn from the cohort of participants.

2.2. Participant recruitment and ethics

As DRM is a multidisciplinary subject, bringing together individuals from varied backgrounds and experiences, it was anticipated that the interview participants would have diverse perspectives. The potential interview participants were identified through our collaborative networks across the DRM sector in New Zealand, and recruitment continued through the snowball sampling technique [74]; each participant was asked to suggest potential participants who would also be suitable to interview.

This research was conducted under a 'low risk' ethics notification (University Human Ethics Committee between May 26, 2022 and August 11, 2022). The initial set of interviews primarily included scientists focused on earthquake and tsunami modelling. To ensure diverse perspectives, we adjusted participant recruitment to encompass a broad disciplinary range in DRM, including disciplinary expertise, such as being a mathematician, a statistician, a hydrologist, a geophysicist, a volcanologist etc. In total, 17 semi-structured qualitative interviews were conducted by the lead author, each averaging an hour, with more than 17 hours of interview data used to analyse these research findings. while the core structure remained consistent throughout the study, some minor adjustments were made based on the scientist's modelling activity. For example, the framing for volcanic modelling was slightly different to the framing for flood modelling.

2.3. Data analysis

As this research focuses on the reflexive experience of the research participants, Reflexive Thematic Analysis [75,76] was adopted during the data analysis.

This method is considered helpful for subjective information, such as a participant's experiences, views, and opinions, and aligns with the data collection method. The first analysis phase involved the familiarisation of data, where the lead author wrote a detailed reflective note for each of the 17 interviews while cleaning the transcripts generated using https://otter.ai.[1] These notes were also taken through repeated listening to this transcript as time allowed. The second phase, Systematic coding, involved coding sections of the transcript in NVIVO[2] Software. These codes were clustered in the third phase to search for the initial themes, which went through several rounds of reflection and discussion with the research team members to develop refined themes in the fourth phase. Four themes were developed and labelled in the fifth phase, discussed in detail in Section 3.3. In the final sixth phase, a report was prepared, weaving together existing literature, the main research questions, and key findings to understand the current uncertainty communication problem. These four categories were primarily constructed through the analysis of the interview data (i.e., through transcription and coding) and associated reflexive discussions [76–78].

The themes from the analysis of the qualitative interview data were developed and given meaning by the lead author. The research questions, data, and the subjective judgement of the researcher through the series of reflexive processes, as discussed earlier, were instrumental in finding the theme. This process resulted in Table 2, which compares how different scientists consider the purpose and focus of their models, their theoretical guidance, and how they understand, manage, and communicate uncertainty, discussed further in Section 3. The process of reflexivity discussed above [76–78] resulted in four broad cross-cutting themes across the interviews: 1) model development and characterisation; 2) Accountability and Opinions; 3) uncertainty communication approach; and 4) collaboration for effective uncertainty communication.

3. Results

In this study, we observed notable differences in how scientists approach modelling, interpret uncertainty, and communicate it, despite their shared overarching goal of providing actionable insights for DRM decision-making. These findings, based on a comprehensive analysis of interview data, underscore the varied ways scientists conceptualise and address uncertainty. Scientists working towards hazard and risk characterisation often focus on quantifying uncertainty through probabilistic metrics or confidence intervals, aiming to provide measurable insights into the likelihood and impact of hazards. In contrast, those modelling the economic and social impact of disasters tend to adopt approaches that embrace uncertainty by acknowledging the limits of quantification and using alternative strategies, such as scenario-based planning or qualitative frameworks, to account for a broader spectrum of possible outcomes.

Based on these observed differences, we categorised the interviewed scientists into three operational domains described as: (1) hazard scientists, (2) risk scientists, and (3) impact scientists. The hazard scientist group included a range of experts, including volcanologists, geologists, geophysicists, and statisticians, who focus on understanding and characterising physical hazards, such as earthquakes, floods, and volcanic eruptions. The risk scientist group comprised professionals such as risk analysts, engineers, and social scientists who work on quantifying the likelihood and potential consequences of hazards, focusing on human exposure and resource vulnerability. The impact scientist group included economists, environmental scientists, and social scientists who primarily evaluate the broader economic, societal, and environmental-related impacts of disasters.

Each modelling domain—hazard, risk, and impact—contributes distinct insights that, when integrated, aim to inform DRM decision-making comprehensively. However, achieving this integration is challenging due to technical difficulties in merging diverse datasets and methods and differences in how these scientific domains conceptualise, address, and communicate uncertainty. We identified that the modelling goals, methodological preferences, and standard norms specific to each domain shape these variations. For example, hazard scientists often emphasise probabilistic forecasting of hazards, risk scientists focus on estimating potential losses due to hazards, and impact scientists aim to capture the social and economic impacts of disaster events. These distinctions influence how uncertainty is quantified, represented, and communicated to decision-makers. The specific perspectives of these three categories are summarised in Table 2.

In this section, we begin by presenting Table 1, which provides an overview of the different scientists interviewed and their interactions with decision-makers. Section 3.1 categorises scientific models based on their inputs and interactions, providing a foundation for understanding their dynamic relationships and feedback mechanisms. Section 3.2 investigates how hazard, risk, and impact scientists approach modelling and address uncertainty, with a summary provided in Table 2. Finally, Section 3.3 delves deeper into the diversity highlighted in Section 3.2 through a thematic analysis. This section explores four key themes derived from interview data: model development and characterisation, accountability and opinions regarding modelling and uncertainty communication, Uncertainty communication approaches, and collaboration of effective uncertainty communication.

Table 1 shows a summary matrix that comprehensively shows the range of the scientists interviewed and their interaction with the decision-makers. This table was developed through a reflective process during the data collection; hence, this interaction should not be generalised to portray the complete picture of the disciplinary range within DRM It is solely based upon the researchers' interpretation.

[1] Otter.ai - Access real-time and shareable meeting notes.
[2] About NVivo (qsrinternational.com)

Table 1
Participants interviewed, their categorisation, modelling focus, and interaction with decision-makers. (The blue square box in the Participants Unique ID row represents the range of their modelling focus. For example, Participant 4 focuses on hazard characterisation, risk identification, and assessment. It also shows how some scientists (but not all) need to communicate with decision-makers. The breadth of the blue box also notes that some scientists may be communicating with other risk, impact, and hazard scientists).

	Hazard Scientist		Risk Scientists	Impact Scientists	Interaction with Decision-Makers
Participant Unique ID	Geophysical and Weather Focus	Hazard Characterisation focus	Risk identification and assessment focus	Impact assessment focus	
1					Limited
2					Limited
3					Limited
4					Limited
5					Intermittent
6					Intermittent
7					Intermittent
8					Intermittent
9					Intermittent
10					Intermittent
11					Limited
12					Intermittent
13					Intermittent
14					Intermittent
15					Intermittent
16					Intermittent
17					Intermittent

Table 2
Scientists' approaches to modelling and uncertainty (This table presents a comprehensive overview, synthesising the key insights gained from reflections throughout the stages of data collection, transcription, and coding of interview data. The table is structured to provide clarity and organisation to the findings. **In the left column,** the distinct narratives that emerged during the interviews are presented. These narratives align precisely with the research questions, directly connecting the study's objectives and the perspectives captured in the data. **The three remaining columns** explore deeper into the categorisation (Hazard Scientists, Risk Scientists, and Impact Scientists) narratives, grounding the observations in the diverse perspectives expressed by the scientists interviewed. Each column represents a fundamental dimension of divergence among the interviewees' views).

Narratives	**Hazard Scientists**		**Risk Scientists**	**Impact Scientists**
Model and Modelling	**Geophysical and Weather Focus**	**Hazard Characterisation focus**	**Risk identification and assessment focus**	**Impact assessment focus**
The central purpose of model design	Understanding the hazardous geophysical and weather phenomena based on the available knowledge.	Will natural hazards pose a risk to human and their resources?	What is the level of risk to human and their resources due to natural hazard event/s?	What is the volume of loss due to disaster event/s?
Outcome of model/ modelling	Identification of the potential State of geophysical and weather systems that is potentially hazardous	Hazard and risk identification	Risk identification and minimisation	Economic and societal costs due to disaster (Examples: Economic impact, Critical infrastructure damage, etc.)
	(Examples: Ground motion simulation, Volcanic ashfall modelling, etc.)	(Examples: Flood hazard map, Seismic Hazard mapping, etc.)	(Examples: Tsunami evacuation mapping, flood inundation Zone, etc.)	
Dominant theoretical guidance towards their approach to uncertainty	PHA (Probabilistic Hazard Analysis theory) is a systematic approach to assessing the probability of exceedance from a hazard. Fuzzy logic theory (This is a mathematical framework that allows representation and manipulation of uncertain sources of a model).	Uncertainty Quantification (how uncertainty in models and data can be quantified and propagated through a modelling process/ identifying the source of uncertainty, quantifying their contribution, and assessing their impact on the final output.	Uncertainty Quantification (how uncertainty in models and data can be quantified and propagated through a modelling process/ identifying the source of uncertainty, quantifying their contribution, and assessing their impact on the final output. However, there is an attempt to move towards system dynamics and use methodological tools like feedback loops and the input-output concept to guide uncertainty sources.	System Dynamics (The study of complex systems and their behaviour. Scientists use complex system theory concepts aiming for a comprehensive understanding of the system, using methods like feedback loops and input-output concepts to understand the uncertainties of a model. Decision theory (how people make decisions under uncertainty) is the dominant guidance from utility maximisation theory.
Primary understanding towards Uncertainty	We do not have enough knowledge and understanding of the complex geophysical and atmospheric systems. (Epistemic Uncertainty)	Our natural system's variability, randomness, or unpredictability are huge, bringing uncertainty. (Aleatory Uncertainty)	The method for acknowledging and communicating uncertainty is hugely defined by "the use of model output'.	Uncertainty cannot be quantified in its real sense. So, it is the subject to be embraced.
The main uncertainty attribute in modelling	Scientific assumption and Expert judgment about geophysical and atmospheric processes.	Modelling Process and choice of processing technique.	Input data that goes into the model.	The dynamic nature of reality and the unpredictable human behaviour.
How is uncertainty characterised and communicated?	Uncertainty Quantification as it helps to reduce uncertainty. Uncertainty is communicated through probabilistic language.		Uncertainty quantification is a common practice. However, elicitation on the number generated from quantification is sought for better communication.	The 'scenarios' are used to communicate uncertainty by capturing a range of possible future pathways. These scenarios help illustrate how different responses may perform under varying conditions, highlighting where specific strategies or outcomes might fail or succeed depending on the uncertainties at play.

3.1. Categorizing models in DRM: A generalised overview

In the DRM landscape, many scientific models play pivotal roles in informing decision-making processes [14,32]. During the interview and through the reflective analysis process, we could categorise the models used in the DRM planning, as shown in Fig. 1. We generalised different modelling groups based on participants' description of their input data and their interaction with modellers in the DRM. Our illustration aligns with Nateghi (2021), where they have described a chain of models and scientists involved in DRM. This is a generalised version of the models used, where each of these scientists in that modelling area, along the modelling chain, shares their output with the following scientists. We are aware that a dynamic relationship exists between various components, such as physics, climate, hazard, risk, impact, and economics [79]. This dynamic process is crucial for understanding the complexity of this modelling process. We also acknowledge that critical feedback loops exist between these different models while operating together to inform decision-making in DRM [35]. However, we have not presented the dynamic relationship and detailed feedback loop between each modelling area, as this paper aims to illustrate the generic picture of modelling in DRM while primarily focusing on uncertainty around scientific modelling.

As illustrated in Fig. 1 below, the DRM modelling community in New Zealand uses a wide range of models. Modelling for hazard prediction is the first step in the modelling chain (e.g., for Geohazard or Weather-related applications). The output of the hazard model is then translated into the input for the risk model and the Economic/Societal impact model. Economic/Societal Impact models also receive inputs from risk models. The role of the risk model is to identify potential risks due to a hazardous event, whereas the impact model focuses on determining the socio-economic impacts in terms of loss and damage to humans and their resources.

In the model chain shown in Fig. 1, we included the engineering model and its interaction with other models, as initially included in our interviews. However, during our analysis and after having reflection on our initial findings, we constrained our participant scope to exclude them from further analysis in this paper. The engineers held a distinctly different viewpoint from the other participants (hazard, risk, and impact scientists), such that they will require a detailed investigation of their own in the future. The transcript below summarises the view of the engineers:

> *"I think the step from hazard to consequence is people believe that that's quite well defined. Whereas, I think it's not well defined in any sense whatsoever. It's completely uncertain. So uncertain that we often won't even make those more widely available because they'll get used incorrectly. It's a false sense of certainty". – Engineer participant*

This interpretation by engineers might also be because engineers bring a practical, solution-oriented perspective, which may sometimes be perceived as a balancing act of engineers between practical need vs theoretical framework, as compared with other scientists, presented in Table 1. This pragmatic perception of scientists is very different from the core narrative discussion of this paper. Hence, our study could not provide sufficient evidence to confirm a direct relationship between their suggestion of practical focus, whether due to the absence of a formal theoretical approach or any other reasons. We thus continue our analysis by focusing on the perspectives excluding the engineers involved in this research. We suggest that future research explore engineers' perspectives on model and model uncertainty through research designed to elicit their unique perspectives, given their different operational practices and demands. We also think this future research will strengthen engineers' contribution to modelling and modelling uncertainty in the DRM.

3.2. Scientists standpoints: unravelling approaches for modelling and uncertainty

The overall goal of modelling is to support decision-making. However, we observed differences among different scientists. This section examines these perspectives from the lens of hazard, risk, and impact scientists, highlighting their distinct approaches towards modelling and uncertainty communication. The summarised version of this is presented in Table 2.

3.2.1. Hazard Scientists

The first category, Hazard scientists, was divided into two sub-groups: one focused on geophysical or climate processes and the other on hazard identification. The hazard scientists concentrate on understanding complex systems and ensuring that the model output aligns with existing scientific knowledge. Probabilistic Hazard Analysis (PHA) theory, as exemplified by seismic and volcanic hazard modelling, has been used as a theoretical approach towards uncertainty [80], as suggested in the transcript below:

> *"Most of the models we use now are probabilistic. So, you are assuming that distribution shape, whatever shape you choose, assuming some smoothing" – A01 Hazard Scientist*

Geophysical and climate hazard scientists view models as only approximations of complex reality around the geophysical process of the earth [32]. Due to the complexity of geophysical and weather/climate systems, there is often limited knowledge. Hence, uncertainty stems primarily from assumptions and expert judgments about natural processes, as illustrated in the statement below:

> "*Even if we have data, at times, properties of these data need to be estimated using expert opinion" – A01 Hazard Scientist*

The hazard characterisation scientist's emphasis modelling endeavours to assess the characteristics of hazards that potentially bring risk to human beings and their assets. This assessment includes creating flood hazard maps or conducting ground shaking analyses or geographic coverage of lahar or ashfall from volcanic eruptions. In all these assessments, probability theory is the dominant, as illustrated below:

> *“We would almost always present our results as a probability. So, it could be an absolute probability, or it could be a conditional probability”- A02 Hazard Scientists*

The two groups have different views on the origin of uncertainty-limited knowledge of complex geophysical and atmospheric systems (epistemic uncertainty) and natural variability or unpredictability (aleatory uncertainty). Key factors influencing uncertainty include scientific assumptions, expert judgment, and modelling techniques. Both groups use uncertainty quantification as a tool to characterise and communicate uncertainty. This includes probabilistic graphs to illustrate reliability, as well as confidence statements that provide a structured way to communicate the degree of certainty or uncertainty in assessments, similar to the approach used by the IPCC. These tools collectively aid in understanding and communicating the reliability of the generated results, as illustrated in the following

> “*So this shows some amount of … … … …, and a probability of exceedance. We give our 80% confidence bounds or 95% confidence bounds. So that’s one way that we’re communicating it*”. *- A01 Hazard Scientist*

3.2.2. Risk Scientist

Risk scientists concentrate on assessing and minimising risks to human life and resources caused by natural hazard events, employing uncertainty quantification to identify and propagate uncertainty through models. This involves creating scientific models, such as those used to map evacuation routes or identification of flood zones. They are primarily focused towards presenting outcomes derived from the interpretation of input data and the accuracy of such data in producing meaningful results, as illustrated in the following statements, where the importance of the data is clearly articulated:

> *"Data is the most useful parameter. I am a strong advocate for the whole garbage in garbage out, if you put rubbish data in, or poorly attributed data. Your model can do anything you want it to do, but you’ve got to put the right inputs in"- B01 Risk Scientist*
>
> *And*
>
> *“What I always think is the key underlying data is hazard data. Some people disagree. Some people believe the vulnerability data is the key, but I think that base hazard data should underlie all the modelling” - B02 Risk Scientist*

Similar to hazard scientists, the risk scientists’ approach also tends to focus on a probabilistic perspective, thereby shaping their modelling approach, as illustrated below:

> *"In the past, there was epistemic uncertainty because different models haven’t been included; there’s been a single model. When we take that to our risk, there’s been a single curve, like I said, probability versus loss. Now, there are 1000s of models that represent different possibilities. So we have 1000s of curves. If you wanted to know the probability of a million-dollar loss, it’s not a single probability. Now, it’s a distribution of probabilities"– B03 Risk Scientist.*

Similar to hazard scientists, risk scientists use uncertainty quantification. However, risk scientists also argue that effectively communicating uncertainty requires eliciting insights beyond the quantified values to support decision-making based on the results generated by their models. Hence, they use different ways to communicate uncertainty, as suggested in the statement below:

> *“We show it in different ways. Some … …. we would present verbally, or we would try and explain to an end user as where the uncertainties are coming in. … ….we would start to show through probability curves and so on”- B02 Risk Scientist*

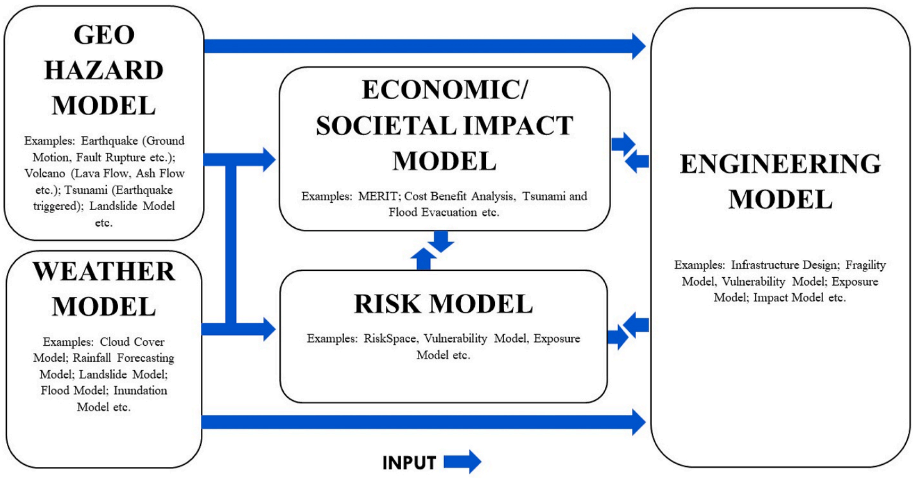

Fig. 1. Model chain used in DRM in New Zealand.

3.2.3. Impact Scientists

The fundamental modelling approach for impact scientists is more holistic and humanistic as they aim to capture the broader societal and economic consequences of disasters, emphasising the unpredictable nature of human behaviour and the dynamic nature of systems, as illustrated below:

> *In the volcanic scenario …., as you trace through from the hazard to the consequence, you can progressively move from physical to human systems ….. and there's different stages in the modeling. There are the physical impacts, but then the next part is working out how long and what's the damage to infrastructure ….. another decision would be around the scenario that we have. As an input says that there will be an evacuation, notice given, so everyone has to leave the region. So that's a decision. We don't know exactly how they will operate" – C01 Impact Scientist*

Impact scientists recognise the difficulty of quantifying uncertainty, particularly given that uncertainties change through time, and suggest embracing uncertainty as an inherent part of the modelling process. Impact scientists suggest that, while communicating uncertainties of these scientific models, communicating multiple scenarios at the outset of the disaster event (to embrace uncertainties in their modelling) would better serve their decision-making purposes [81], where they also acknowledge the inherent limitations in reducing uncertainty in models 'as illustrated in the statements below:

> *I think there's a limit to how much you can reduce that uncertainty. And actually, I think what we need to do the opposite. We need to embrace the uncertainty. So that's when you start to talk about things like using future scenario. Actually it's not about making the model as accurate as possible, it's actually making sure that the model represents the breadth of outcomes that could occur. - C02 Impact Scientist*
>
> *and*
>
> "*We're trying to reduce uncertainty when it's fundamentally impossible to reduce that uncertainty.*"*- C05 Impact Scientist*

3.3. Thematic analysis- diverse perspectives of scientists'

This section explores the nuances of distinct approaches taken by hazard, risk, and impact scientists, emphasising the areas highlighting thematic areas for navigating scientific modelling and uncertainty. This section encompasses four themes developed through reflective thematic analysis [82]: model development and characterisation, accountability and opinions, uncertainty communication approaches, and collaboration for effective uncertainty communication. Through these lenses, we decipher how differences among various scientist groups contribute to challenges in communicating uncertainties, and the way forward for effective communication within model-based decision support for DRM contexts.

3.3.1. Model development and characterisation

The 'model development and characterisation' theme discusses the broader issues of creating and refining models while gaining a deep understanding of models' behaviour and performance and their use. We observed that the complexity surrounding the model conceptualisation and use of the model by the different scientists leads to a different approach to uncertainty communication among the scientists interviewed for this research.

Hazard scientists highlight the limitations in our knowledge and capacity to predict natural events, pointing out the challenges of the changing assumptions about geology and weather and the difficulty in understanding associated uncertainties. For example, hazard scientists focused on subjective judgement and assumptions about the earth and weather behaviour, like earthquake geology in seismic hazard modelling [32] or geochemical data in volcanic ash cloud modelling [83]. These approaches are also shaped by observations of how hazards propagate, enabling scientists to anticipate the cascading effects of initial events. Despite efforts to incorporate complexities like topography and physical variations, hazard scientists assume that huge uncertainties persist in those hazard models. Hazard scientists, while acknowledging that data used in modelling efforts are not perfect and carry uncertainty, stress that, at times, imperfect data is their only option, as suggested here by one of the participants:

> "*There's no option. So, there's a situation for us as a modeller - this is what the data is, so how do you compare the data to what you want out of it! So, you're always stuck with the same, it's not you go out and look for data, it's just there. You just have to work with what you've got". – A01 Hazard Scientist*

Hazard scientists also highlight that there is no hard data in hazard modelling. Instead, all the data are model outputs of other models based on various inputs, such as expert opinions and assumptions. This suggests a high degree of subjectivity is involved [84] in the process of creating these models. For example, the following statement by the Seismic hazard model illustrates the role of subjectivity in modelling.

> *"The earthquake catalogue tells you the magnitude and location and a time. But that's something that happened at depth, and we're on the surface. So it's an estimate, using a model of what the magnitude is, and when you use a different type of estimate, you get a completely different number. And they all mean something different" – A02 Hazard Scientist*

Risk scientists view the purpose and process of developing a model as a crucial factor that dictates the emergence and propagation of uncertainties. This is consistent with the discussion in Ref. [50], which highlights the importance of modelling context. The different modelling context demands different approaches for communicating uncertainty. Thus, comprehending the specific context in which a scientific model is applied is essential for effectively communicating the uncertainties of these models.

Risk Scientists view that understanding the model's purpose and its development process is essential in determining the levels of uncertainty. Risk scientists highlight a critical consideration in scientific modelling, particularly bringing narrative from earthquake modelling: defining the boundaries of the study area. The speaker notes that the choice of study bounds can introduce biases into the model and significantly impact uncertainty, which is illustrated by the statement below.

> "*One of the big things we have is where to draw study bounds, and how that bias's the model. So normally, what we do there is, take basically the area that's been shaken by an earthquake, the strongest area, but obviously those waves spread out across the whole world. So how big an area you take, and how does that bias your model? So that can often be a big factor for uncertainty*". *– B04 Risk Scientist*

Impact Scientists also advocate the importance of the modelling 'context', like Risk Scientists. However, they are much more driven by the fact that models cannot perfectly replicate the real-world [1,8] due to uncertainties in both the data and the models themselves.

> "*A model is always a simplification of reality. There's always trade-offs and choices that you're needing to make in terms of what you put in your modelling. All models are wrong, they're just inherently wrong*". *– C01 Impact Scientist*

These Impact Scientists are more concerned that the iterative nature of model development, where data is chosen based on the model's purpose and assumptions, plays a crucial role in defining model boundaries and its use. The challenges lie in effectively communicating uncertainties related to assumptions, as these assumptions often dictate the model's scope and critical relationships. Impact scientists aim to move from the conventional thinking of data-centric and statistical models as they highlight the role of assumptions, as illustrated below:

> "*Sometimes as we will model the things that we can to the 9th degree because there is data available, and we do have the skills and the capabilities to do it, and it's interesting. And then we might have a giant assumption for something else … … … …. that so often it's easier to do the thing where we have the skills and the capability and so there is a bit of a risk that people can fall into doing that*". *– C01 Impact Scientist*

However, the training and knowledge acquired over years of education and practice, predominantly rooted in statistical thinking [11,85,86], appear to constrain their ability to embrace this shift wholeheartedly.

3.3.2. Accountability and opinions

The theme broadly discusses issues related to scientists' responsibility and how they perceive the roles of other scientists in relation to uncertainty communication. Drawing on the core theme' accountability and opinion,' we discuss the key contributors to the disconnect that leads to the uncertainty communication problem.

We identified that different scientists have different theoretical guidance, understanding, and approaches towards uncertainty, as described in Table 2. Even among Hazard Scientists, the two sub-groups identified (geophysical and weather-focused, and hazard-focused, *see* Table 2) have different approaches towards uncertainty. Those focused on hazard identification have a more statistical way of approaching uncertainty [87,88]. Meanwhile, those focused more on geophysical and weather focus adopt models that consider laws and rules of physical systems science in their approach to uncertainty [89]. While both use quantification methods, they have different understating of sources of uncertainty. The randomness or unpredictability of our natural system, which is also often referred to as aleatory uncertainty [90], is referred to as the primary source by hazard-focused scientists, while scientists focusing on physical science point towards our fundamental science knowledge as a primary source, often referred to as epistemic uncertainty [86], as illustrated below:

> "*We just don't know what's going on. So uncertainty isn't in the data range. It's in the fundamental, unknown physical that's I worry about most I think*". *– A01 Hazard Scientist*

In addition to that, and also discussed in Section 3.2.1, expert judgment is used as input data [91], where uncertainty quantification techniques are used to reduce uncertainty. This situation has led to a discussion among hazard scientists as they debate the appropriate application of statistical methods designed for numerical data to subjective judgments made by experts. New Zealand's National Seismic Hazard Model illustrates this, which relies on fault characterisation data derived from various geologists [32]. Expert judgement can be argued as necessary to fill in gaps in data [92]. However, this can also lead to a higher degree of uncertainty in the model, which is difficult to capture using statistical methods.

Risk Scientists, in the other side, prioritise data in modelling [93] as the primary source of uncertainty, potentially discounting other uncertain areas within a modelling space.

> "*I'm a strong advocate for the whole garbage in garbage out, if you put rubbish data run, or poorly attributed data. Your model can do* anything you *want it to do, but you've got to put the right inputs in*". *– B01 Risk Scientist*

This statement by a risk scientist, highlighting 'input data' as a primary source of uncertainty, could be interpreted as shifting the focus of uncertainty to hazard scientists. While this perspective reflects the interconnected nature of hazard and risk models, it underscores a potential challenge in uncertainty communication. Placing more emphasis on input data may unintentionally assign disproportionate responsibility for uncertainty to hazard scientists, mainly since risk models often rely on data generated by hazard models. This dynamic highlights the need for collaborative approaches to address uncertainties across disciplines rather than attributing them to specific stages of the modelling process [28]. Meanwhile, Risk Scientists also highlight the broader discussion on the need for more dynamic and adaptable approaches to modelling, recognising that data alone may no longer be sufficient to address the complexities and uncertainties posed by a changing climate, as illustrated below:

> "*The biggest assumption that I make in my models is that what has happened in the past is going to happen in the future … … …. But I think that assumption is going to be heavily tested over the next coming decades with climate change*". *– B04 Risk Scientist*

Impact Scientists appear to have more experience handling model variables that are more subjective as their models focus on understanding human behaviour and impacts, handling more tacit data sources. The Impact Scientists' main goal is to understand the effect of hazard and risk events on the overall societal and environmental system [94]. They deal with the problem systematically, aiming to unravel the intricate interactions and dependencies within these systems [79]. Their approach involves a thorough analysis of the context surrounding uncertainties, seeking to identify not only the direct effects of such events but also the cascading consequences and interrelated factors that contribute to the overall impact. As they sit at the right end of the modelling chain, depicted in Table 2, they are bound to think more about the compounding factors of uncertainty throughout the model chain and the impacts of those choices. The following two statements depict the difference in the approaches between the risk and impact Scientists:

> "*Definitely an input. And this is where I think all of us working in risk probably have our own ideas. I definitely think that uncertainty comes in every single step of modelling. But I think it's really important to understand the hazard first, because a lot of the uncertainty comes in from hazard space*". *– B02 Risk Scientist*

> "*I think the data is the last thing that you think about. Really, when you when it comes to model construction? I think you really need to be thinking about what is the problem that you're trying to solve?*" *- C01 Impact Scientist.*

Another reflection from the transcript concerns understanding and communication, which have definite traction among all the different scientific groups. Thus, huge expectations and responsibilities lie in their associated practice. All the participants in this study duly agree on the importance of modelling in their respective areas. However, there is a divide in the ways they express and understate the primary source of uncertainty. One of the Impact Scientists' transcripts effectively summarises this.

> "*You've the hazard modelers, they're using a lot of past data, and it's all getting quite specific, and there's probabilities. The more and more information they have, they get more and more confident about what is going to happen. And then the impact guys come and say, this could be but there's so many different variables about what this could actually look like in terms of landslide generation, it depends what the weather is, it depends how is the soil profiles, depends on the all these other things. And then they think that there's so much uncertainty. And then the socio-economic consequences, we come along, and we're like, this is all about human behaviour. It depends on, who's in government at the time, or what the economic conditions or what disasters have lined up before that event, just as so many variables?*" *– C02 Impact Scientist*

3.3.3. Uncertainty communication approaches

The third theme, 'Uncertainty communication approaches,' focuses on the strategies and methods scientists use to acknowledge and communicate uncertainties and how this has created a problem in 'uncertainty communication' for DRM decision-making.

Scientists interviewed in this research acknowledge the pervasiveness of probability as the primary tool for quantification, reduction, and communication of uncertainty. Probabilistic language is used by all scientist groups, which broader researchers adopt as a framework to manage and communicate uncertainty [95–99]. This approach has faced criticism and confusion amongst scientists, who emphasise that uncertainties cannot be described by probabilities only [100,101]. Although there is continued disagreement about the suitability of probabilistic language to express uncertainty [46], scientists have a dominant view that "Probability is what scientists have" to acknowledge and communicate uncertainty, which is elaborated below from a statement by a Hazard scientist.

> "*So maybe it's you could argue whether or not it's good or not. But it's what we know. So that is the ultimate answer is a probability. So, you can frame it in other ways. But ultimately, what we have is a probability*".*- A01 Hazard Scientist*

While hazard scientists suggest that probability is an excellent tool and what they have for uncertainty communication [95,102], risk scientists suggest that it might not be as effective when communicating with decision-makers [96,103–105]. The rationale behind employing probability for quantifying and reducing uncertainty is also discussed in line with the challenge of effectively communicating uncertainty verbally; however, risk scientists support articulation using words [96], as also evident in IPCC reports. This was evident in our research with Risk Scientists:

> "*People have tried utilising things when dealing with uncertainty, a descriptor like it is very likely that happen, or it is extremely likely, or extremely unlikely. So that's kind of what they use at the moment".- B05 Risk Scientist*

Impact scientists expressed concern that probabilistic methods solely address uncertainty in model quantities and ignore uncertainties in model structure because people do not separate the probability and magnitude components of risk. They argue that hazard and risk scientists opt for probabilistic ways, assuming some distribution shape on their data [83], and suggest despite probabilistic reasoning being the dominant basis for understanding and communicating uncertainties [83,106] methods also create confusion among decision-makers. For example, the common language of "1 in the 100-year event' used by hazard and risk scientists is heavily criticised by impact scientists.

> "*I find that with some of this, tsunami evacuation or volcanic modelling, you're often presented with a single model result, which then maybe phrased as this is just a single scenario, the probability is still 1 in 100, or 1 in a 1000-year event, which honestly is less than meaningless to most people".- C05 Impact Scientist*

Impact scientists suggest that it would be better to acknowledge the uncertainty and explain what degree of uncertainty has been reduced using those techniques [107,108]. They suggest that communicating multiple scenarios is helpful for decision-makers to make informed decisions while recognising the limitations posed by uncertainty.

"*Probabilities is hugely difficult for a lot of people to understand and to comprehend, which is why I would be tending to use more scenario. My best case, worst case, middle, or if this happens, then this is the likely outcome*". *- C01 Impact Scientist*

3.3.4. Collaboration for effective uncertainty communication

The fourth theme, 'Collaboration for Effective Uncertainty Communication,' focuses on the ways scientists are collaborating, the challenges, and their importance. Despite the diverging views on the above three themes, the need for collaboration among scientists for effective uncertainty communication has a collective voice.

Uncertainty communications are targeted to help decision-makers [3,109]However, the scientists share different collaborative experiences in our research. This different approach seems mainly due to their work in their niche, which is highlighted in statements below:

"*Collaboration are based on projects. Projects have defined the level of collaborate*". *- A01 Hazard Scientist*

"*We're working with district and city councils where we collaborate actually quite extensively throughout to check our assumptions*". *- B01 Risk Scientist*

"*I spent a lot of time talking with them about how they would like those outputs produced and how they would, and what they want. It tends to vary, it varies by what they're planning to use the model for*".*- B04 Risk Scientist*

Hazard scientists share their collaboration experience within scientific projects, and often revolve around specific tasks or objectives, which define the degree and nature of interaction. Whereas, some Risk scientists emphasise the importance of iterative collaboration with councils to validate assumptions, while others highlight the need to tailor outputs to users' specific needs. This variation in collaborative approaches reflects the diverse priorities and methodologies within scientific domains, underscoring the need for adaptable strategies to bridge uncertainty communication gaps. However, the statements below by impact scientists highlight the need for better collaboration and emphasise the need to understand and interpret the complexity surrounding uncertainty.

"*By involving decision makers in or at least allowing them to look at and better understand how projections or scenarios or modelled results are produced, that can then build their own capability in terms of handling complex uncertainty information working with probabilities, communicating some of those results to key stakeholders and constituents, etc. Rather than it being that kind of delivery model where we produce some model output and just give it to them, and then ask them to just trust us that". – C05 Impact Scientist*

"*The key thing in terms of working together is that everyone uses different language. They call something that I don't call something. Most of our problems are in just trying to explain where the connections happen*". *– C03 Impact Scientist*

"*A real balance needs to be struck of not overloading the decision maker, with so much uncertainty information that actually all it's doing is creating noise. So it's a balance. And I think that is where the Scientist, and the decision maker actually needs to be collaborating between them to design, how model information is presented*". *– C01 Impact Scientist*

Impact scientists advocate for involving decision-makers in the modelling process to enhance their capacity to interpret and communicate uncertainty. Additionally, they stress the necessity of developing a shared language to bridge domain and disciplinary gaps and caution against overwhelming decision-makers with excessive uncertainty information, advocating for a balanced approach. Collectively, these insights emphasise the critical need for collaborative frameworks that address the complexities of interpreting and communicating uncertainty.

4. Discussion

A significant aspect that emerges from this research is the lack of uniformity in approaching scientific modelling and uncertainty treatment, which is often discussed in the literature due to the complex nature of the scientific modelling process [19,32]. It is widely acknowledged that scientific models are only approximations of reality [13,21], which is also evident in our research, and the application of their models is subject to significant uncertainty [110]. We also identified that there is a shared understanding and acknowledgement that diverse viewpoints exist between scientists, and the challenge lies in reconciling these contrasting modelling dynamics and communicating uncertainty for better decision-making [111,112].

In DRM decision-making, models are often employed either for forecasting and prediction, such as climate models that generate projections of key variables [113,114], or for policy and planning, focusing on interventions within complex systems [1,81]. However, we would like to acknowledge that this dichotomy between anticipatory modelling (pre-emptive) and post-event response modelling (post-facto) may no longer fully capture the needs of a changing hazard landscape. DRM increasingly requires both approaches, as they are not mutually exclusive but interdependent, forming a complementary modelling system. Addressing both dimensions within an integrated framework better reflects disaster management's dynamic and evolving nature. This interplay is reflected in Table 2, where scientists on the left side are more hazard-focused, leaning toward prediction and forecasting. These scientists emphasise anticipatory approaches to understand and address hazards pre-emptively. In contrast, scientists on the right are more impact-focused, favouring policy and planning interventions, which aligns more closely with addressing the consequences of hazards and planning adaptive responses. The contrasting perspectives illustrate the necessity of bridging the gap between these approaches, fostering integration to effectively support both anticipatory and reactive needs in DRM.

Model characterisation has been identified as a complex area in model-based decision-making as early as Walker et al. (2003) [115], and this discussion has been further advanced by Refs. [53,116,117]. Similar concerns have also been shared in DRM modelling, which aligns with what we observed in this research [3,8,118]. Although all scientist groups in this research agreed about the complexity involved in the modelling, they have different interpretations of uncertainty sources, as guided by their respective approach to model development and characterisation (See Table 2). This divergence contributes to communication challenges, highlighting the need for a unified uncertainty communication framework that incorporates decision-makers' needs.

It appears that the complexity of communicating uncertainty and the training of the scientists has led them to favour a quantifiable approach. This inclination towards numerical methods reflects a perception that quantifying uncertainty provides a clearer and more consistent means of understanding and addressing it [119,120]. These methods allow for comparison across multiple events and ensure uniformity in the analysis. However, addressing uncertainty should not be confined to communication alone; the focus must also lie on how this information can be applied during decision-making processes [121]. Tools designed to address uncertainty during decision-making, rather than merely communicating it, are essential. For example: Tools designed to stress-test decisions under varying assumptions and conditions are essential for adaptive and resilient decision-making [122]. These tools help prevent over-reliance on fixed assumptions that could later prove inadequate or incorrect. By integrating scenario-based stress-testing and hazard-specific approaches into uncertainty frameworks, decision-making in DRM can better accommodate the unique characteristics of each hazard and the inherent complexities of uncertainty. These tools help avoid decisions relying on a fixed set of assumptions, which could prove inadequate or incorrect later. By integrating such tools, decision-making can remain adaptive and resilient in uncertainty.

Interdependencies between uncertainties, especially for multi-model approaches, as discussed in Table 2, and cascading hazards create evolving uncertainties that can eclipse outcome uncertainties [5]. It is not only the relationship between scientists and decision-makers that presents challenges in uncertainty communication. It is evident from this research that the relationship and communication between different scientists also create a barrier to uncertainty communication. Different uncertainties in a scientific model can have a different impact on the model outputs and are rooted in different sources [123,124].

Hazard and risk scientists share similar approaches towards characterising and communicating uncertainty, which are primarily aligned with a probabilistic way of thinking towards uncertainty [37,125]. However, there are differences between hazard and risk scientists in understanding the key source of uncertainty. Risk scientists emphasise that it is influenced by natural stochastic uncertainty (the variability of the system). In contrast, hazard scientists emphasise epistemic uncertainty (lack of knowledge), which aligns with the discourse of other researchers [5,64,126], while impact scientists have a different approach, suggesting scenario approaches [18]. On the one hand, different scientific groups manage uncertainty based on their disciplinary approaches. On the other hand, they recognise the existence of differing approaches of other scientific groups. However, their dominant ideas still guide the current practice of acknowledging and communicating uncertainty. This paradox is a barrier to effectively communicating model uncertainty for better DRM decision-making.

Doyle (2015) suggests that when using probability, the probabilistic language should fit people's cognitive frame, making information more accessible to understand. Regarding uncertainty communication, we also suggest that statements like "probability is what we have" have limited scientists' ability to explore approaches beyond probability. Probability should not be the only tool for communicating uncertainty, which aligns with the research findings in environmental assessment [127] and the weather forecast [99]. We argue that the use of probability in uncertainty communication has also narrowed scientists' perspectives towards a focus on quantification, which, in turn, has contributed to scientists' not having a shared understanding of uncertainty and has created a barrier to uncertainty communication for better decision-making in DRM.

The other divergence observed was the tendency across the range of scientists interviewed to push uncertainty into an unknown unknown [128], which suggests uncertainty is beyond their scope of work, creating a lack of clarity and understanding. Scientists express biases and disagreements, contributing to misunderstandings and conflicts in uncertainty communication, where every scientist has their own subjective biases over other scientists in the chain. For example, hazard scientists use probabilistic methods to estimate uncertainty from input data [32,129], where they push uncertainty communication discussions towards incorrect assumptions or limited system understanding [60]. Risk Scientists generally prioritise robust data [130,131], and in that process, the uncertainty discussion moves towards the data generation process. Impact scientists pay attention to the unpredictable nature of human behaviour [132]. Although all scientists operate within the umbrella of DRM, their disciplinary training seems to have framed their approaches towards uncertainty. Risk scientists tend to emphasise on data-driven methods, often framing uncertainty in terms of aleatory uncertainty [130]. Hazard scientists, on the other hand, often attribute uncertainties to gaps in knowledge, aligning more with epistemic uncertainty [9]. Despite acknowledging the importance of modelling for decision support, this divide between aleatory and epistemic [133] has led to conflicts and challenges in effective communication. These disparities likely arise from the differences in training, perception, and their daily scientific endeavour. However, our reflective processes have not delved deeply into this, which is certainly an area for further research.

Another common thread observed in our research among the scientists is that each one believes their modelling or expertise is more than complex than others. This has led to biased views on, 'how to communicate uncertainty?' The bias makes them choose one uncertainty analysis method over another in terms of importance and, thus, what and how they then choose to communicate. This can create misunderstandings and conflicts in communication among scientists themselves [134]. For example, Hazard scientists are more entrenched in the technical aspects, like physical science, which primarily approaches uncertainty from a probabilistic standpoint [51]. Conversely, impact scientists approach uncertainty with a broader scope to embrace uncertainty [48]. This dichotomy has become increasingly evident in recent decades as decision-makers seek advice in unprecedented disaster events, where all these groups of scientists are consulted as and when needed.

Scientists also agree that different degrees and types of uncertainties are present in different modelling fields [65,66], and there should be a different approach for communicating these uncertainties beyond the current method based on probabilities. Our observation amongst participants on the need for diversification beyond the current practice of uncertainty communication using statistical language and reducing uncertainty can also be attributed to the desire to move for a common communication approach. Hence, uncertainties can stem from various sources, such as errors in statistical analysis, ambiguous or limited data, oversimplification of complex risk information, disagreement among scientists, and lack of knowledge [135,136]. However, there is a consensus amongst Scientists on the need for tools and frameworks that effectively support the communication of uncertainty alongside model outputs.

The current communication problem is rooted in the lack of an effective communication mechanism, which Doyle (2019) has suggested as an uncertainty typology. A poor communication technique may even be misleading for decision-making. Communication of uncertainty requires utilising a variety of knowledge bases from many sources [137]. Thus, effective solutions must blend various knowledge-making approaches, including formal and informal, accredited and lay, and experiential and conceptual understandings.

Despite the diverging views discussed above, a familiar voice amongst scientists working in DRM highlights a need for ongoing collaboration from the early stages of model development and throughout the entire process of model development, as has been suggested by other researchers [138–140]. DRM, being a complex and multifaceted field, requires better collaboration between science and society, as also suggested by other researchers [109,141,142]. Our finding closely aligns with the field of landscape ecology, as researched by Ref. [142], who highlighted that collaboration is key for uncertainty discussion in modelling efforts. Therefore, we suggest that future research should critically examine these varying approaches by different scientists, significantly when theoretical concepts diverge, as highlighted in our study. Future research also necessitates exploring the underlying assumptions or delving deeper into the contextual factors that give rise to these different approaches. Addressing these discrepancies is essential for resolving them, ensuring a coherent narrative, and maintaining the integrity of uncertainty communication. It might also signal areas for further exploration or clarification within the academic discourse. Handling these conflicts thoughtfully is key to presenting a robust and convincing uncertainty communication mechanism.

5. Conclusion

Modelling as a tool for decision-making better serves its purpose, provided the uncertainties in the modelling process are properly accounted for and communicated to the model users. Currently, there is no uniform framework to communicate model information and uncertainties between scientists and decision-makers. However, it is clear that most modelling endeavours seek to inform and support decision-making but may be limited in that goal due to inconsistent approaches to communicating uncertainty. The diverse scientists in DRM have different disciplinary and experiential training, experience, and exposure with the decision-makers, influencing their choices for communication of uncertainty. Individual disciplines usually have unique approaches to, and standards for, modelling and, likewise, the practice of handling and communicating uncertainty. Hence, the challenge of uncertainty communication is exacerbated by the scientists themselves. This challenge stems from scientists' diverse approaches to uncertainty and modelling and a need to identify a uniform communication framework across these groups. The disparity in approaches to uncertainty leads to varied forms of communication. This increases the potential for miscommunication, leading to communication barriers and creating challenges for decision-making.

CRediT authorship contribution statement

Annal Dhungana: Writing – original draft, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Emma Hudson Doyle:** Writing – review & editing, Supervision, Funding acquisition. **Garry McDonald:** Writing – review & editing, Supervision. **Raj Prasanna:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare the following financial interests/personal relationships that may be considered potential competing interests: Annal Dhungana, Emma Hudson Doyle, and Raj Prasanna report a relationship with Massey University that includes employment. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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