Guidelines for climate uncertainty quantification and communication

Deliverable 2.8

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About Climateurope2

Timely delivery and effective use of climate information is fundamental for a green recovery and a resilient, climate neutral Europe, in response to climate change and variability. Climate services address this through the provision of climate information for use in decision-making to manage risks and realize opportunities.

The market and needs for climate information has seen impressive progress in recent years and is expected to grow in the foreseeable future. However, the communities involved in the development and provision of climate services are often unaware of each other and lack interdisciplinary and transdisciplinary knowledge. In addition, quality assurance, relevant standards, and other forms of assurance (such as guidelines, and good practices) for climate services are lagging behind. These are needed to ensure the saliency, credibility, legitimacy, and authoritativeness of climate services, and build two-way trust between supply and demand.

Climateurope2 aims to develop future equitable and quality-assured climate services to all sectors of society by:
- Developing standardization procedures for climate services
- Supporting an equitable European climate services community
- Enhancing the uptake of quality-assured climate services to support adaptation and mitigation to climate change and variability

The project will identify the support and standardization needs of climate services, including criteria for certification and labeling, as well as the user-driven criteria needed to support climate action. This information will be used to propose a taxonomy of climate services, suggest community-based good practices and guidelines, and propose standards where possible. A large variety of activities to support the communities involved in European climate services will also be organized.

Executive Summary

Uncertainty must not be hidden, downplayed or ignored. This report will provide the reader with a toolkit of strategies to quantify and communicate uncertainty in the context of climate services. The recommendations provide the insight needed to tailor uncertainty information and messaging to fit both the decision context and the audience.

The content of this report is presented in a series of thematic tables of recommendations. Each table of recommendations is prefaced with introductory text to provide the reader with an understanding of the context for the recommendations within. Source materials are provided for each recommendation, we advise readers to visit the source materials in order to explore the recommendations in more depth.

Through being as open as possible about uncertainty, uncertainty can be used as a tool to build trust and encourage curiosity in the support of sound decisionmaking.

Keywords

Climate services, Uncertainty, Communication, Quantification, Risk, Assessment, Vulnerability, Deep Uncertainty

Disclaimer

This report is not based on a comprehensive, structured literature search and the authors do not claim an exhaustive or infallible interpretation of all referenced studies. The recommendations in this report are based on a selection of the scientific literature on the topic of uncertainty in the context of climate services, supplemented with insights from interviews. Please refer to the original sources for a more comprehensive insight and/or a more detailed discussion.

Introduction

This document is part of the collection of resources provided by the Data and Processes work package (WP2) team within the Climateurope2 consortium. While the primary focus of this specific text is to provide recommendations on uncertainty quantification and communication, it serves as part of a broader series. We encourage interested readers to explore the full collection of final WP2 documents, which will be accessible via Zenodo and the Climateurope2 website upon publication.

The upcoming deliverables in this series include:

Table 1: Upcoming deliverables in the Data and Processes work package (WP2)

Expected date	Deliverable Title
March 2026	**Deliverable D2.6**: Guidelines of good practices for vocabularies, formats, metadata and technical standards
March 2026	**Deliverable D2.7**: Good practices in provenance of processing methodologies and ways to communicate it in a user-friendly manner
April 2026	**Deliverable D2.9**: Common procedures for data verification, certification and quality management
April 2026	**Deliverable D2.10**: Guidelines on how to enhance data, tools and knowledge for climate impacts, extremes and risks through standardisation of climate services

The background work on this topic can be found in the Climateurope2 deliverable "Update to D2.3 Preliminary best practices in climate uncertainty quantification and communication" (1). That preliminary work identified a set of eight main lessons:

1. Always start with the most relevant risks for the target population
2. A standard approach to uncertainty assessment and communication is needed
3. Use language the audience is familiar with (don't say uncertainty)
4. There are multiple ways to evaluate and communicate uncertainty
5. Communication about uncertainty builds trust
6. Precision of information should be relevant to the situation
7. Understand existing narratives
8. Be aware of deep uncertainties

This report is a synthesis of the findings from that work augmented by findings from a further review of the literature and also from interviews with climate service providers. The thematic tables of recommendations provide the main structure for this report. Each table of

recommendations has a brief introductory text, providing the reader with an understanding of the context for the recommendations within. Source materials are provided for each recommendation, we advise readers to visit the source materials in order to explore the recommendations in more depth.

The focus of this report is on the climate sciences, however, many of these recommendations are applicable to any field. General recommendations can be found in the first table of Recommendations for uncertainty communication and the first table of Recommendations for uncertainty quantification. With the recommendations presented here we hope to be able to provide the reader with the information needed to be as open as possible about uncertainty, so that uncertainty can be used as a tool to build trust and encourage curiosity in the support of sound decisionmaking.

Recommendations for uncertainty communication

General communication recommendations

Approaches to communicating uncertainty will inevitably depend on the context of the communication. Here we present the most general and broadly applicable recommendations categorised by the following thematic contexts:

- Education and Explanation
- Personal Experience and Narratives
- Clarity, Transparency, and Trust
- Framing the Message
- Communication Strategy
- The Need for Standardised Approaches

A recurring message is the need for transparency. Uncertainty must not be hidden, downplayed or ignored.

Table 2: Comm.1: General Uncertainty Communication

ID	Recommendation
Education and Explanation	
Comm. 1.1	**Match the complexity of information to the user's climate education** **Recommendation:** • Use simple messages and intuitive graphics in public communication. • Be clear about what the uncertainty information refers to. • Provide information about why climate projections are intrinsically uncertain. • Only use technical language and complex graphics with sophisticated users. • If jargon is necessary it should be explained. **Rationale:** • Some users may simply wish to know whether the forecast event will happen or not. These users are not interested in probabilistic predictions and will often view such predictions as an attempt to avoid responsibility and to "hedge bets". In the absence of a categorical yes/no forecast, this type of user may turn to the probabilistic forecast and translate it into a categorical one. Such users are less likely to understand the sources of uncertainty and will prefer simple messages and graphics. [5] • Effective user education can provide an appropriate understanding of why many climate-related issues, and methods are not an exact science. Co-production processes provide an opportunity to educate about climate uncertainty. Where user education is not possible, communications should aim for an intuitive understanding of climate uncertainty. • Sophisticated users of uncertainty information are aware of the underpinning reasons for uncertainty and, when providing this information, service providers

	can use technical language and speak in some detail. The use of relatively complex graphics is also possible. [5] Nevertheless if jargon is necessary, remember to explain it. [2] ● A remaining challenge is for users to understand what the probability of occurrence actually refers to. Is it at a point? Over a spatial area? Over time? **Sources:** [2, 5]
Comm. 1.2	**Use consistent numerical scales** **Recommendation:** Use consistent numerical scales when using large numbers. **Rationale:** It can be difficult for users to compare uncertain quantities especially when the numbers are large. The difference between 1 million and 1 billion is clearer if the latter is expressed as 1,000 million. **Sources:** [2]
Comm. 1.3	**Combine plain language with objective uncertainty information** **Recommendation:** An effective strategy for consistent understanding of uncertainty information is to use objective numerical measures of uncertainty (e.g. probabilities), in combination with plain language that is clearly defined. **Rationale:** ● While the IPCC reports are an essential means of quantifying scientific uncertainty, a series of studies have found that people severely underestimate the meaning of some probability statements (e.g., 'very likely'),while overestimating the probability of others. [3] ● It has been shown that the way people interpret and describe uncertainty information can be influenced by the significance or magnitude of the predicted event [77]. For example, if light rain and heavy rain are both objectively forecast to have a 10% chance, people describe the heavy rain event subjectively as being more likely. ● People often expect this exaggerated behaviour in others and so will "decode" what they are told. Thus, when receiving a forecast that describes a high-impact event as a medium likelihood, users will often assign a lower threat level due to a belief that the provider of the forecast was exaggerating. [5] ● Meanwhile other studies have shown that people's perception of the standardised IPCC likelihood phrases tend towards interpretations that are more middling than the phrases' intent [31], [32], [59]. ● It is important to bear in mind both the tendency of users to "exaggerate" the likelihood of high intensity events and the tendency of users to underestimate the extremes of standardised uncertainty language. **Sources:** [3, 5, 31, 32, 59, 77]
Comm. 1.4	**Shape communication towards the language the audience is familiar with** **Recommendation:** Use commonly understood descriptive language in place of scientific terminology. Illustrate concepts with contextualised examples. **Rationale:** ● The vocabulary of science can have very different meanings in public life, for instance, the word "uncertainty" can imply ignorance. ● In some instances it can be better to use commonly understood descriptive language in place of scientific terminology. For instance, the presence of

	uncertainty could be conveyed with the word "range", and a likelihood could be expressed using the framing of odds rather than a percentage. [1] • Describe ranges as showing uncertainty, with narrower ranges as having greater certainty. • Multiple contextualised examples also help to clarify understanding. • It is not necessary to avoid using the word "uncertainty" altogether. However, accompanying it with a clear definition or brief explanation supports understanding. **Sources:** [1, 21]
Personal Experience and Narratives	
Comm. 1.5	**Provide context to give probabilistic predictions relevance** **Recommendation:** Accompany a probabilistic prediction with a comparison to the usual frequency of such events. **Rationale:** One of the particular challenges for users of probability information is having a reference point for the information. This is particularly important to assist with interpretation and response. For example, a prediction such as "60% chance of a storm this afternoon" is enhanced if a message such as "this is about twice the normal chance for this time of year" is attached. **Sources:** [5, 21]
Comm. 1.6	**Move from the abstract to the concrete** **Recommendation:** Link climate uncertainty to concrete risks from specific impacts with individual relevance or highlight analogies with other types of familiar risk. Use case studies and personal narratives to engage people who do not have direct experience of extreme events. **Rationale:** • Uncertainty is not an inherent barrier to decision making. Decisions about risk management in the contexts of health, insurance and national security are decisions under uncertainty. However, the concept of climate change itself can seem abstract to many. • Link climate to concrete risk from specific impacts with individual relevance or highlight analogies with other types of familiar risk, so people are better able to weigh up the costs and benefits of action versus inaction. • The tangible and traumatic experiences that arise from extreme weather events reduce the 'psychological distance' between people and climate change, allowing affected communities to relate more easily to the issue, as they will have to deal with similar risks in the future. • The use of case studies is a good way to engage people who haven't experienced extreme weather events directly. Engage users with personal narratives. • When climate change is present in the stories that people use to discuss their lives, and what they expect from the future, information about individual climate impacts will more easily slot into them. **Sources:** [3]
Comm. 1.7	**Tell a human story not just a statistical one** **Recommendation:** Use storylines and narratives to provide comparisons with earlier

	experienced events (e.g. 'we have seen this before, therefore what could happen in the future') to help people to imagine possible futures and think concretely about rare events that have not yet been experienced. [35] **Rationale:** • Storylines and narratives can help people to envision multiple possibilities and make rare events salient. • Episodic recollections (e.g. recalling experiences of severe weather) can be more salient and elicit greater engagement than purely semantic thinking (e.g. recalling facts about a 1 in 1000 year event). [35] • People have a tendency to prioritise daily personal experiences over statistical learning so telling human stories about the people affected by climate change (and how they are responding to it) shifts climate change from a scientific to a social reality. [3] **Sources:** [3, 35]
Clarity, Transparency and Trust	
Comm. 1.8	**Be specific about what exactly is uncertain** **Recommendation:** • Be specific about whether uncertainty is due to incomplete understanding of a process, unreliability of measurements, insufficient data, or other sources. • Do not leave readers with sweeping statements which make it sound like nothing can be trusted. **Rationale:** • To manage ambiguity aversion and avoid casting a shadow of doubt over everything we say, it is important to localise where exactly there is a level of uncertainty. [2] • Uncertainty about the magnitude of specific climate impacts in specific locations can be conflated with broader uncertainty or disconsensus about climate change. Care needs to be taken to avoid this. [3] • It may be useful to highlight where strong consensus and low uncertainty exists as well as where there is greater uncertainty. **Sources:** [2, 3]
Comm. 1.9	**Use communication about uncertainty to build trust** **Recommendation:** Be transparent about the uncertainty evaluation of the information. Make it clear when there is a level of uncertainty about the data. Do not gloss over variance and evidence gaps. **Rationale:** • Uncertainty is something to be managed and normalised, not hidden. • The existence of high uncertainty should be seen as a reason to engage with information, particularly if it relates to a vulnerability. • Climate services should be transparent about the uncertainty evaluation of their information. • With an awareness of uncertainties comes an ability to assess risks more critically. More confidence can be placed in assessments of risk that are clear, in spite of the uncertainties.

	• Even if uncertain, a given risk might need to be acted on, because the potential consequences are unacceptably large. • Transparency about the quality and limitations of data is a duty owed by anyone putting information out to the public to inform individual decision making. • Where there is high uncertainty but no feasible opportunity to communicate it to the relevant decision-maker, there is a danger that modelling can no longer serve transparency or robust decision-making. **Sources:** [1, 2, 29]
Comm. 1.10	**Test your communication methodology** **Recommendation:** If you can, trial or test your messages first to see how they are received. **Rationale:** There is no substitute for audience research when it comes to constructing successful climate messages, and using language that resonates with the people you want to engage. **Sources:** [3]
Comm. 1.11	**Use trusted communicators and be clear about scientific consensus** **Recommendation:** • Select communicators who are trusted by the intended audience. • Understand the drivers of their existing views about climate change and frame messaging to resonate with existing concerns. • Have clear and consistent messaging about the scientific consensus. **Rationale:** • Try and find the closest match between the values of your audience and those of the messenger. • With topics that have become politically charged people may filter scientific facts according to their own political views. Uncertainty around climate change tends to be perceived as higher amongst those with right-leaning political values. • Discussing climate and therefore climate services in terms of risk-aversion, resilience and security may resonate more strongly with decision makers with centre-right political orientations than environmentalist frames. • Likewise, be aware that people with different worldviews and political orientations may differ in the sources and communicators they trust. • Having a clear and consistent message about the scientific consensus is important because some research suggests it is a 'gateway belief' that affects whether people see climate change as a problem that requires an urgent societal response. • Use a graphic such as a pie chart to visually enhance the message. **Sources:** [3]
Comm. 1.12	**Manage your audience's expectations** **Recommendation:** • Use analogies from 'everyday life' so people can see that uncertainties are everywhere. • Emphasise that science is an ongoing debate to prime users to expect uncertainty.

	• Address any mismatch between the expectations of decision-makers and the ability of models. **Rationale:** • Science is often presented by the media or taught in schools as a series of definite facts and figures. As a consequence, people have different expectations about uncertainty in science, relative to 'everyday' situations where uncertainty is seen as a given. Scientists will never know everything about a subject but this does not mean that they know nothing. • Different people reading the same uncertain information may reach different conclusions. • One study found emphasising that 'science is a debate' as opposed to 'science is a fixed body of facts' influenced people's motivation to act on uncertain messages. Participants who understood that 'science is a debate' were less likely to dismiss messages containing uncertain information. • Uncertainty will not always undermine the effectiveness of science communication, as long as it fits the audience's understanding of how science works. • Address any mismatch between the expectations of decision-makers and the perceived ability of models to make predictions meaningful to policy on regional scales. Models that appear reliable when it comes to predicting averages might not be so reliable when it comes to predicting rare events. **Sources:** [3, 29]
Comm. 1.13	**Understand existing narratives** **Recommendation:** Understand how people are thinking about risk and decision making. Work with humility and transparency to co-create new climate narratives or storylines of plausible futures. **Rationale:** • People use narratives to capture the essential meaning of complex evidence. Until the existing narratives and how people are thinking about risk and decision making are well understood, it is very hard to introduce actionable climate information and related services. • Once there is a clear idea of existing narratives, it is key to build trust through mutual learning, embrace the diversity and contradictions of people with competing views and understanding, and work with humility and transparency to co-create new climate risk narratives or storylines of plausible future events. **Sources:** [1]
Comm. 1.14	**Improve representation in the modelling community**. **Recommendation:** Widen the discourse on model validation with a broad geographical representation of participants. **Rationale:** Modelling is a quantitative way to create narratives about the future, and narratives empower us to intervene in these futures via shared cultural imaginaries. Participants from regions that are most vulnerable to climate change should be included in that process. **Sources:** [29, 86]
Framing the Message	

Comm. 1.15	**Start with what is known** **Recommendation:** In climate communication, start with what is known and follow with uncertainty information and caveats. **Rationale:** ● Too often, climate scientists find themselves apologising for what they don't know, rather than confidently communicating what they do know. Uncertainty at the frontiers of science should not prevent focus on the 'knowns'. ● In climate change communication it is better to begin with what is known. ● Lead with scientific findings i.e. take-home messages (with confidence terms) and follow with explicit uncertainty (ranges, scenario dependence, scale limits). ● e.g. "all climate scenarios show that temperatures and extreme precipitation increase, even though there are some uncertainties", rather than "there are many uncertainties about climate change, but we know that temperatures will change". **Sources:** [1, 3]
Comm. 1.16	**Be aware that the framing of risk and uncertainty matters** **Recommendation:** Frame an uncertain situation in terms of risk reduction through action to increase intention to act. **Rationale:** ● People respond to functionally identical information differently depending on how it is framed. ● For instance framing an uncertain situation in terms of risk reduction through action (e.g. 'if we act now the chance of destructive winter floods occurring is 20%) rather than risk if no action taken (e.g. if we do not act now the chance of destructive winter floods occurring is 80%) was found to increase intention to take some form of risk reduction action. ● While climate services may not wish to promote a particular course of action or inaction it is critical to realise the effect that framing can have. **Sources:** [3]
Comm. 1.17	**Frame climate impact information in terms of 'when' rather than 'if'** **Recommendation:** Frame climate impacts in terms of uncertainty about when they will occur. **Rationale:** ● Climate impacts may be perceived as more concrete and less psychologically uncertain when presented in terms of the range of time in which an impact will happen rather than the the likelihood of an event happening at a specific point in time ● E.g. "sea levels will rise by at least 50cm and this will happen between 2060 and 2093" rather than "by 2072 sea levels will rise between 25 and 68cm with the average being 50cm". **Sources:** [3]
Communication Strategy	
Comm. 1.18	**Use vulnerabilities to identify relevant risks**

	Recommendation: Use an exploration of vulnerabilities to identify the most relevant climate risks. **Rationale:** ● An exploration of vulnerabilities can be used to discover which climate risks are of most concern. ● From there a climate communication practitioner (ideally in collaboration with the clients they are supporting) can discern which aspects of climate information are most relevant to those risks and hence the relevant uncertainty space to describe. ● To support the work of climate communication practitioners a climate service provider will need to provide sufficient information to enable the relevant uncertainty information to be extracted. **Sources:** [1]
Comm. 1.19	**Different media, different methods** **Recommendation:** Choose a communication method that is fit for the media type. **Rationale:** The choice of method and format for communicating uncertainty information will depend greatly on the media being utilised. What works well in one communication medium may not be effective in another (radio, television, social media, reports). However, consistency should prevail. **Sources:** [5]
Comm. 1.20	**Communication strategies depend on the decision context.** **Recommendation:** ● Identify the type of decision and the facts relevant to that decision. Characterise the relevant uncertainties, assess their magnitude, draft possible messages, and evaluate their success. ● If awaiting a signal for action, communicate both the uncertainty in the science and the decision rule. ● If choosing among fixed options, characterise uncertainties and communicate the factors that were taken into consideration and also those that were excluded. ● If learning to create options, communicate the science relevant to creating the options, uncertainty is part of that. **Rationale:** ● For scientists, uncertainty obscures theoretical questions. For people who rely on science, uncertainty obscures choices. A strategic approach to the structure of the communication will bring some clarity. Three classes of decision. ● **Awaiting a signal for action** (e.g., whether to evacuate before a hurricane). Communicate both the uncertainty in the science and the decision rule translating the science into a recommendation. Those awaiting a signal for action need to know whether the evidence is certain enough to pass the threshold defined by their decision rule. ● **Choosing among fixed options** (e.g., which medical treatment is best). Characterise uncertainties. The detailed level will depend on the sensitivity of the recipient's decision to the information. Communicate the factors that were taken into consideration and those that were excluded. Those choosing among fixed options need to know how far to trust predictions of valued outcomes.

	• **Learning to create options** (e.g., how to regulate nanotechnology)? Communicate the science relevant to creating options, uncertainty is part of that. Those creating options need to know how well the processes shaping their outcomes are understood. **Sources:** [15]
Comm. 1.21	**Develop a range of communication methods** **Recommendation:** Develop a range of methods to communicate uncertainty. **Rationale:** Uncertainties need not only to be analysed and described but also communicated. The information needs to be sufficient to use and not mis-use the data product. To limit the overload potential it can be useful to have a range of methods with which to communicate uncertainty and then to use those methods that are most relevant to the decision situation. **Sources:** [1, 38]

ID	Research Gaps
Gap.1.1	**Develop a standard approach for uncertainty descriptions** **Recommendation:** A standard approach should consider not only the climate science components, but also the complexities regarding socio-economic vulnerability, and hence social sciences should be involved. **Rationale:** • The scope of climate science is broad. The implications of its findings need to be understood by many different research communities and also be communicated to wider society. • A standard approach to describing and quantifying uncertainty will facilitate the passing of information between different communities of practice. • Such an approach should consider not only the climate science component, but also the complexities regarding socio-economic vulnerability, and hence social sciences should be involved. **Sources:** [1]
Gap.1.2	**Adopt a standard reporting protocol for uncertainty** **Recommendation:** Adopt a standard reporting format for communicating uncertainty information. **Rationale:** • A standard reporting format for summarising uncertainty information, that experts can learn to create and decision makers can learn to use, would provide clarity about what information to include in communications. • A proposed protocol for a summary format [15]: Step i) Identify key outcomes for decision makers (e.g., stroke) and how to measure them (e.g., annual probability). Step ii) Summarize variability Step iii) Summarize internal validity Step iv) Summarize external validity Step v) Summarize the strength of the basic science

	Step vi) Summarize uncertainty (e.g., 95% credible interval) • Produces statements of the form, "Considering the variability of the evidence (step ii) and my assessments of the internal validity of the studies that collected it (step iii), their relevance to the decision-making domain (step iv), and the strength of the underlying science (step v), I am 95% certain that the true value of the critical outcome (step i) is between Y and Z." • This proposed protocol for uncertainty information places the information about what is known towards the end of the statement. This is contrary to previous recommendations that recommend that uncertainty communications should be framed by describing what is known first. **Sources:** [15]

Written and/or verbal communication

The language of uncertainty may itself be a source of confusion. Be consistent and take active steps to reduce the cognitive load required to understand the information you are providing. Highlight the information that is most important and combine qualitative expressions with quantitative information and vice versa.

- Foreground the most important decision-relevant information
- Explain any conditions that affect prediction quality
- Collaborate and co-produce
- Compare like with like
- Use percentage likelihoods as well as return periods
- Explain percentage expressions
- Supplement qualitative descriptions with numeric information
- Express quantitative uncertainty with a numeric range
- Shape communication towards language the audience is familiar with

Table 3: Comm.2: Written and Verbal Uncertainty Communication

ID	Recommendation
Comm. 2.1	**Foreground the most important decision-relevant information** **Recommendation:** Ensure the most critical information is the most salient. **Rationale:** • Where a briefing style is used, the summary at the start should contain the most decision relevant elements of the forecast. This could include the likelihood of decision relevant threshold exceedance, spatial resolution of forecast, and any user-specific advisory statements provided as part of the forecast. • It has been found that readers pay most attention to information in summary boxes, with limited attention to more detailed text and diagrams.

	Sources: [20]
Comm. 2.2	**Explain any conditions that affect prediction quality** **Recommendation:** Explain any conditions that affect prediction quality. Address any mismatch between the expectations of decision-makers and the ability of models. **Rationale:** ● Forecast quality can be conditional on external sources of predictability, such as ENSO, meaning that forecast models may perform better in some years than others. ● To avoid confusion and loss of trust that may result from variable forecast quality, it is recommended that forecasters explain if forecast performance (forecast skill) is conditional on external sources of predictability (e.g. precipitation forecasts for the Middle Yangtze are more reliable in El Niño years). ● Address any mismatch between the expectations of decision-makers and the perceived ability of models to make predictions meaningful to policy on regional scales. **Sources:** [20, 29]
Comm. 2.3	**Collaborate and co-produce** **Recommendation:** Engage actively with information users and phase the delivery of content. **Rationale:** ● Working with decision-makers over a long period of time, and collaborating to co-produce information has been found to create shared understanding. (19) ● The integration of climate information into decision-making should be rooted in deep engagement that respects and values multiple types and elements of knowledge and encourages deliberation around diverse perspectives and agendas. (55) ● The challenge extends beyond communication and rests in developing new understanding and knowledge amongst climate scientists, other scientists, decision makers and other contextual experts (55) ● Mental models could be a useful way to identify how people understand climate information and improve communications (56). **Sources:** [19, 55, 56]
Comm. 2.4	**Compare like with like** **Recommmendation:** Use consistent denominators to communicate ratios **Rationale:** ● Use a consistent common denominator to improve the understanding of comparative likelihoods. e.g. use "1 in 10" and "2 in 10", rather than "1 in 10" and "1 in 5". ● This may be relevant when talking about future risks such as floods and their return periods which are often communicated as a "1 in 100-year event" or "1 in 5-year event." ● The choice of common denominator needs to ensure that all the likelihoods you want to compare can be expressed clearly. ● This recommendation only holds true if the likelihoods have comparable

	magnitudes. If one event is '1 in 1000' and another is '1 in 10', using 1000 as the denominator would force you to say '100 in 1000', which is harder to interpret. **Sources:** [19]
Comm. 2.5	**Use percentage likelihoods as well as return periods** **Recommendation:** Combine return periods with percentage expressions **Rationale:** ● It has been shown that people can misinterpret the likelihood of a risk when it is communicated only as a return period especially if that event has occurred recently. ● Users may think a flood is less likely when one has just occurred or more likely when it has not, leading to a "flood is due" effect (57). ● Using an additional percent chance expression reduces the "flood is due" effect. **Sources:** [57]
Comm. 2.6	**Explain percentage expressions** **Recommendation:** Explain percentage expressions, do not assume that they will be correctly interpreted. **Rationale:** ● Many people, including experts and scientists, misinterpret probabilities and statistics. When communicating uncertain future climate information, it is important to try and reduce the mental load of interpretation for all involved, including scientists. ● In a study with participants from climate-adjacent UK organizations, 79% and 46% of participants described probability estimates as a feature that hindered their understanding of maps and graphs, respectively (58). ● When communicating climate projection probabilities and statistics (such as relative change or percentiles) care should be taken to explain them and not assume that they will be correctly interpreted by people, even those who are in the field of climate change. **Sources:** [19, 58]
Comm. 2.7	**Supplement qualitative descriptions with numeric information** **Recommendation:** Use qualitative descriptions with consistency and supplement them with numeric information. Provide access to underlying data where possible. **Rationale:** ● The language of uncertainty may itself be a source of confusion. What, for example, is the difference between "chance of" and "possible"? ● Under-appreciation of the natural variability in people's intuitive understanding of the phrases used to convey uncertainty can create "an illusion of communication" and undermine the quality of subsequent decisions. ● Verbal expressions are useful for indicating the general direction of travel, and it is important to use them with consistency. However, supplementing verbal terms with numerical likelihoods reduces ambiguity in interpretation because the terms are better differentiated. ● The IPCC has a calibrated language and framework for confidence and likelihoods which include quantitative and qualitative descriptions [59]. However, IPCC authors have disagreed on how to communicate probabilistic

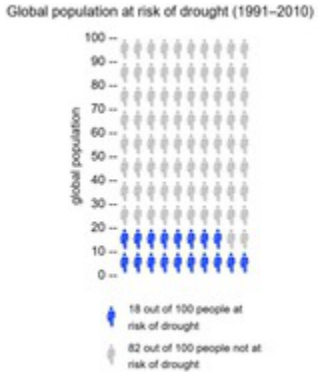
	information [60] and the public systematically underestimate IPCC likelihood statements [31], [32] • Qualitative descriptors for probability (e.g., "very likely") are not as well understood as quantitative descriptors (e.g., 90%–100% likelihood). • Do say, for instance, "global warming is likely (66% chance) to reach 1.5°C between 2030 and 2052 if it continues to increase at the current rate". • Provide access to underlying data where possible. **Sources:** [2, 5, 19, 31, 32, 59, 60]
Comm. 2.8	**Express quantitative uncertainty with a numerical range** **Recommendation:** Express quantitative uncertainty using a numerical range after the primary value **Rationale:** • Using words like "estimated" and "around" alongside a primary value, such as a mean or median, only conveys a vague sense of uncertainty which can easily be forgotten. • Do say, for instance, "unemployment is estimated at 3.9% (between 3.7% and 4.1%)" at least when you introduce the statistic for the first time. Don't just say "unemployment is estimated at 3.9%" expecting readers to understand the implied uncertainty. • For more clarity, describe what the uncertainty range conveys (e.g. 90% interval, min-max, Ignore outliers?) **Sources:** [2, 21]
Comm. 1.4	**Shape communication towards language the audience is familiar with** **Recommendation:** Use commonly understood descriptive language in place of scientific terminology. Illustrate concepts with contextualised examples. **Rationale:** • The vocabulary of science can have very different meanings in public life, for instance, the word "uncertainty" can imply ignorance. • In some instances it can be better to use commonly understood descriptive language in place of scientific terminology. For instance, the presence of uncertainty could be conveyed with the word "range", and a likelihood could be expressed using the framing of odds rather than a percentage. [1] • Multiple contextualised examples also help to clarify understanding. • It is not necessary to avoid using the word "uncertainty" altogether. However, accompanying it with a clear definition or brief explanation supports understanding. **Sources:** [1, 21] (Repeated from table Quant.1)

Visual communication

Here we present recommendations for the visualisation of uncertainty. Although our focus is on the climate sciences, these recommendations are applicable to any field. In the section above we noted that, in written communication, uncertainty phrases are best understood when accompanied by percentage probabilities. Here we present: a proposal for a visualisation of

probabilities using icon arrays; an overview of quantitative uncertainty visualisation methods; a recommendation to present an even number of future projections; recommendations about using the same presentation method for both past and future; uncertainty on maps; a reminder to use colour appropriately and considerately; a brief introduction to infographics; and a 12-step strategy for uncertainty visualisation. We recommend that readers visit the source materials in order to explore the recommendations in more depth.

Table 4: Comm.3: Visual Uncertainty Communication

ID	Recommendation
Comm. 3.1	**Icon arrays enhance comprehension of probability** **Recommendation:** Visualise percentages using coloured icons in an array. **Rationale:** ● In the icon array, each icon represents a specific percentage (e.g. a rectangular array of 100 icons each representing 1%) .  Figure 1. Icon array for the representation of percentages (Craig et al. 2025). ● Although such visualizations are not widely used for communicating climate projections, icon arrays could be tested as an effective and new method for climate communications. ● IPCC graphics have been critiqued by some as being too complicated. Icon arrays might be a simpler option for future documents. **Sources:** [19, 61, 62]
Comm. 3.2	**Incorporate uncertainty into graphs and charts** **Recommendation:** ● Where uncertainty measures are available, show the data, but also their uncertainty, by incorporating the uncertainty into the visualisation method. ● The choice of chart-type depends on the data pattern. ○ a line chart communicates the development over time of a statistic ○ a bar chart communicates the comparison of sizes and ○ a point chart communicates differences in value **Rationale:** ● **Error bars** have the benefits that the visual focus is on the point estimate and that the confidence interval is a detail. Error bars allow the comparison of the sizes of the uncertainty intervals for different estimates. Many academics have

	been trained to use plots with error bars, making them a popular well understood method. • **Error bands** on line charts are essentially continuous error bars and convey the variation of uncertainty over time. Describe their range as "showing uncertainty" with narrower ranges as showing "greater certainty". • **Box plots and violin plots** are useful for visualising distributions but are less useful for depicting uncertainty, because they have no central point estimate. • **The Gradient approach** encodes probability using colour intensity (the more likely, the more intense the colour) and is a popular choice for time series, especially for future predictions. • **Cross section graphs** such as the bar graph can be used to convey an uncertainty distribution via the application of a complementary cumulative distribution which shapes the tips of the bars. • **'Spaghetti' plots** (Hypothetical Outcome Plots) explicitly plot multiple outcomes and are useful for showing prediction uncertainty. They make it clear that the future (or estimation) is not set, and that one of multiple outcomes is possible. Such plots do not encode the full uncertainty distribution but work well to convey the presence of uncertainty. • **Frequency Distribution** plots show the likelihood of occurrence (probability) of events of a certain magnitude (which can be absolute, or a difference from the mean) that occur over a certain period. Such distributions generally form a bell-shaped curve with the mean (average) located in the middle. **Sources:** [1, 4, 21, 86]
Comm. 3.3	**Quantitative uncertainty visualisations can be understood by the public** **Recommendation:** Error bars and error bands are the most well understood methods of uncertainty visualisation. **Rationale:** • One common line of thinking is that the public do not understand uncertainty or confidence intervals and that showing these confuses them. • However, Tak et al. (2013) found that most users are able to read uncertainty visualisations and have an understanding of them. Users that had some statistical education were more equipped and at ease with indications of uncertainty. • The most well-understood methods of uncertainty visualisation found by Tak et al. (2013) were error bars and error bands, but to their slight surprise the 'spaghetti' plots were also effective. • Spaghetti plots seem to be suited for depicting prediction uncertainty, they highlight that the future is not set, and that there are multiple possible scenario's, some of which are plotted. **Sources:** [4, 64]
Comm. 3.4	**Present an even number of projections** **Recommendation:** Present an even number of climate projections to avoid the misattribution of likelihood. **Rationale:** • Climate communication practitioners should be aware of the impact of visual information. An audience will often interpret the middle or central projection of

	future climate as being the most likely when in fact no likelihood can be attributed. ● To avoid this bias, practitioners can present an even number of projections. Giving an even number of projections implicitly encourages the audience to think about which of the projections is the most relevant for their topic of interest. **Sources:** [1, 63]
Comm. 3.5	**Use consistent visualisation methods for both historical past and projected future** **Recommendation:** Present historical data and data for the projected future using the same method. **Rationale:** ● In climate science it is common to present future climate projection statistics with 30-year-mean box plots and to use time series plots with an error band to represent the historical period. Whilst box plots are a scientifically correct representation of future climate, it is confusing for consumers of climate information to have the past and future presented in different ways. ● Presenting historical data using the same method as data for the projected future makes the interpretation of the information more intuitive. ● E.g. using colour to represent the quartiles of the recent temperature distribution and using the same absolute temperature thresholds for colour boundaries on the projected changed distribution to highlight the increased likelihood of extremes. **Sources:** [1, 29, 86]
Comm. 3.6	**Represent year-to-year variability on historical visualisations** **Recommendation:** Include year-to-year historical variability on the historical proportion of graphical visualisations of historical and projected climate trends. **Rationale:** ● For many people, the year-to-year variability of the climate system (uncertainty due to internal variability) is more important and impactful than the slow shift of long-term climate means. Information about a projected future can be made more tangible and less abstract when it is framed in the context of the lived experience of the audience. ● Include year-to-year historical variability on the historical proportion of graphical visualisations of historical and projected climate trends. This provides context for users by demonstrating what the variability they have experienced looks like in the context of the information that is presented about the future. ● For time series plots, this could be done with the use of 90% shading to show both the variability of the past climate as well as that of a projected future, with data for the year-to-year variability of the historical period overlaid. ● For box plots this could be done by overlaying the historical statistics via annual data points. **Sources:** [1, 63]
Comm. 3.7	**Incorporate uncertainty into maps** **Recommendation:** Convey scenario uncertainty with multiple maps, convey model uncertainty with layered content such as shading or hatching.

	Rationale: • Maps can convey layers of information, allowing the geographic change of a quantity (such as temperature) to be displayed using colour and also the uncertainty of that change using a pattern. • However, if the communication only provides one map instance, it would convey an implicit bias towards the chosen scenario. • The presence of scenario uncertainty of the future climate can be conveyed by showing at least two map instances from different scenarios. **Sources:** [1, 21]
Comm. 3.8	**Use colours with care** **Recommendation:** Colour information should align with intuitive interpretation. Use neutral colours where probabilities are close to 50%. Be mindful of users with colour vision deficiencies. **Rationale:** • It is common practice to use colour in the graphical presentation of probability (or other uncertainty) information. Care should be taken that the colours that are used send the intended message. • Colour information should align with intuitive interpretation e.g. blue for high hydrological extremes and red for low hydrological extremes. • When conveying probability information, it is recommended to use a colour scale that has a neutral central section (grey or white), where probabilities are close to 50%, with colour intensity increasing towards more 'emotive' colours at the upper and lower probability extremes. • Avoid use of rainbow colour scales, they create false emphasis at colour boundaries. • Be mindful of users with colour vision deficiencies. Avoid using both red and green on the same chart for example in rainbow colour scales. Test graphics with a colourblindness simulator. **Sources:** [5, 85]
Comm. 3.9	**Infographics provide an overview of diverse content** **Recommendation:** Use infographics to convey aesthetic and well-explained information about climate projections or storylines. **Rationale:** • Infographics can be used to provide aesthetic and well-explained information about climate projections. • Uncertainty is implied by presenting more than one projection for the future climate. • Infographics are able to provide an overview of often complex multi-sector information such as climate projections, climate impacts and climate adaptation options. • Infographics are a useful tool for co-production processes, they can be used to start a conversation and to summarise findings.

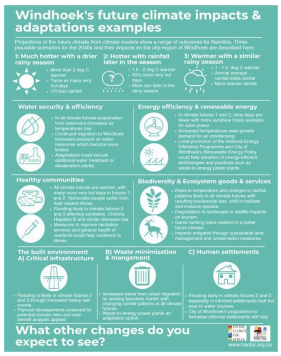


Figure 2. Climate Risk Narrative infographic developed through the FRACTAL Windhoek Learning Lab process (Jack et al. 2020)

Figure 3. Four scenarios for climate change in the Netherlands. The number of small blocks represents the extent of climate change around 2100 compared to 1991-2020 (KNMI, 2023).

Sources: [19, 55, 63]

Comm. 3.10

Have a Strategy for Uncertainty Visualisation
Recommendation: Have a strategy for uncertainty visualisation and test it with users.
Rationale:
Using a strategy to decide the most appropriate visualisation method can bring clarity to your information exchange. Gathering audience opinions about the visualisation method is important if you want to know whether it worked and how to improve it.

- 1. Identify the visualisation task
- 2. Understand the data
- 3. Why does it need to be visualised?
- 4. Who is the user and how will the visualisation help them?
- 5. Which uncertainty should be visualised?
- 6. Decide on a definition of uncertainty.
- 7. What are the specific causes of the uncertainty?
- 8. What are the causal categories of the uncertainty?
- 9. Determine the visualisation requirements.
- 10. Prepare uncertainty for visualisation
- 11. Try different techniques
- 12. Does the visualisation work? Get audience opinions and criticisms. If necessary, go back to 10 and 11 to adjust.

Sources: [24]

Comm. 3.11	**Communicate through images and stories** **Recommendation:** embrace narratives and art to convey uncertainty **Rationale:** ● While the IPCC reports are an essential means of quantifying scientific uncertainty, a series of studies have found that people severely underestimate the meaning of some probability statements (e.g., 'very likely'), while overestimating the probability of others. ● The reality is that most people understand the world through stories and images, not lists of numbers, probability statements, or technical graphs, and so finding ways of translating and interpreting the technical language found in scientific reports into something more engaging is crucial. ● A visual artist can convey uncertainty concepts that can't be quantified and can present concepts such as sea level rise in a more engaging way than graphs alone yet still be factually accurate if climate projections are used to inform their work. **Sources:** [3, 29]
Comm. 3.12	**Foster interdisciplinarity** **Recommendation:** Foster interdisciplinarity, especially for designing interactive visualisation formats, and information to inform public action. **Rationale:** ● Visualisations can influence viewer judgments in ways that the designers did not anticipate. ● When developing visualisation formats, or other means to communicate uncertainty, it can be helpful to work with other disciplines especially in respect of interactive visualisation formats. ● There is evidence that visualisation of uncertainty affects many aspects of decision making; for example, choices about the graphical presentation of hurricane forecasts have been shown to influence people's decisions on whether or not to follow evacuation orders. ● Visualisation designers should seek to develop visualisations that account for the complexities in decision-making. ● Is the uncertainty visualisation driven by what "you" think users need to know or by what the users have asked to know? **Sources:** [29, 78]

Recommendations for uncertainty quantification

General quantification recommendations

Climate services typically involve multiple processing steps, ranging from the generation of climate data or climate model output through post-processing, downscaling, derivation of indicators, impact modelling and the generation of user-oriented products. Each step can introduce additional sources of uncertainty, while some existing uncertainties may be reduced, transformed, or made more explicit. Not all uncertainties can be quantified or formally propagated through the entire value chain; some arise from structural assumptions, incomplete knowledge, or factors beyond current modelling capability. The recommendations in this section focus primarily on uncertainties that can be assessed and communicated in a quantitative manner.

Table 5: Quant.1: General Uncertainty Quantification

ID	Recommendation
Quant. 1.1	**Be comprehensive** **Recommendation:** Evaluate uncertainties in all steps of the processing chain **Rationale:** Evaluating uncertainty in climate modelling, for example by analysing a multi-model ensemble like CMIP, is now a well-established best practice. But uncertainty can be in all processing steps that are typically applied to climate data, from measurement to downscaling and bias correction of model output, to the formulation of appropriate indicators or decision metrics. Well-established methods and approaches to evaluate and - to the extent possible - quantify uncertainty are available for all steps in the climate data processing chain, and should be applied as appropriate. **Sources:** [1,22]
Quant. 1.2	**Propagate uncertainties** **Recommendation:** Propagate relevant uncertainty through the full workflow **Rationale:** Uncertainty should be propagated through the full workflow, and not re-estimated independently at each step. In practice this could mean propagating individual ensemble members through the processing chain (from models to downscaling and bias correction, to indicator calculation), or explicitly adding the uncertainty estimate from the previous step to each new step. In reality this often means that the range (or envelope) of uncertainty expands at each step of the process to the extent that potential impacts and their implied adaptation responses span such a wide range as to be practically unhelpful. In such a case it may be helpful to reduce the uncertainty, for example by partitioning the sources of uncertainty or constraining the analysis to a specific climate impact. This should be made clear to the user. **Sources:** [1,39]
Quant. 1.3	**Appropriate precision** **Recommendation:** Precision of information should be justified by the underlying uncertainty and should be relevant to the decision context

	Rationale: Reporting precision or level of detail (resolution) that exceeds the information content of the data or models can create a false sense of accuracy. Overly precise information can also lead to perceptions of disagreement and to distrust.The precision or level of detail of the data should match what is justified by the underlying uncertainty and limitations and should support, rather than distort, interpretation. This extends to the outcomes of an uncertainty analysis itself: even if a quantitative analysis is possible, it may not always be appropriate, or it may not be necessary to pass the outcomes numerically to the user. **Sources:** [1, 41, 42]
Quant. 1.4	**Deep uncertainties** **Recommendation:** Be aware of deep uncertainties **Rationale:** The conventional approach to representing uncertainty in climate services is probabilistic, typically based on ensembles of climate model simulations. In the face of deep uncertainties, the limitations of this approach are becoming increasingly apparent. It is therefore important to extend existing methodologies to include strategies for accounting for and communicating deep uncertainty, including the recording of assumptions made in the analysis process and evaluating the impact of these on the final outcome or decision, and the co-creation of narratives or storylines to improve risk awareness and strengthen decision-making. **Sources:** [1, 8, 43, 45]
Quant. 1.5	**Be transparent** **Recommendation:** Record assumptions and limitations where uncertainties cannot be quantified **Rationale:** Not all sources of uncertainty can be expressed quantitatively, particularly those related to choices and assumptions in the methodology, data gaps, or deep uncertainty. Explicit documentation of assumptions and limitations ensures transparency, supports informed interpretation, and prevents misrepresentation of confidence. For example, an implicit assumption in many bias correction techniques is that biases found in the simulation of the past climate (typically by comparing the model simulations with observations or observation-based datasets) will be similar under future - and often very different - climate conditions. If the sensitivity of the outcomes/results/products against such assumptions are not tested, then at least they should be made explicit. **Sources:** [1, 45]
Quant. 1.6	**Follow established practices** **Recommendation:** Follow established practices for evaluating model uncertainty **Rationale:** Climate models are subject to different sources of uncertainty, and different approaches have been developed to evaluate and/or quantify these uncertainties. Commonly used methods include the use of multi-model ensembles (such as CMIP) to evaluate structural uncertainty in the model formulation; perturbed-parameter ensembles and similar sensitivity analysis techniques to quantify the effects of parameter uncertainty; initial conditions ensembles (or large ensembles) to quantify the effect of uncertainty in the starting conditions; and scenario analyses to separate out the effects of future emissions, land use and socio-economic pathways. The appropriate

	methods should be followed depending on the application; for example, initial condition uncertainty is especially relevant for near-term climate prediction. **Sources:** [1]
Quant. 1.7	**Model ensembles** **Recommendation:** Model ensembles should be composed and processed transparently **Rationale:** Especially when dealing with multi-model ensembles, the results depend strongly on choices made in the composition and treatment of the ensemble. This includes aspects such as model selection, model dependence, the use of weighting schemes, and the effect of ensemble size. An explicit consideration of these aspects has the potential to improve the interpretability and robustness of the results, but methodological choices should be transparently documented and the sensitivity of the outcomes to these aspects should ideally be evaluated to avoid misleading results arising from correlated models, subjective weighting or small ensemble sizes. **Sources:** [1] **Relevant to:** Knowledge systems **Evidence level:** 1
Quant. 1.8	**Evaluate skill** **Recommendation:** The skill of a model or ensemble should be evaluated against observations where feasible, and uncertainty estimates should be evaluated for statistical reliability and physical plausibility **Rationale:** Comparison with observations provides the primary basis for assessing the credibility of model output, and the skill of a model or model ensemble should be evaluated wherever feasible. This also applies to uncertainty estimates in order to determine whether their magnitude is appropriate. An evaluation of the reliability and physical plausibility of both model results and uncertainty estimates helps ensure internal consistency and guards against outcomes that are statistically or physically implausible, particularly where observational constraints are limited. **Sources:** [47]

Expert assessment (and its combination with evidence)

Expert-elicited judgements can characterise less predictable, or less explored, elements of the climate system and expert-elicited reasoning provides additional information and knowledge that is absent from modelling approaches [51].

Structured approaches to expert elicitation tap into the wisdom of the crowd and also mitigate against social pressures such as the presence of a dominant, persuasive personality, the tendency to want to meet the approval of the group and the unwillingness to change an opinion which had been publicly expressed [50].

There is often an assumption that scientists share views on uncertainty but formal elicitations can reveal surprising differences. Sources of uncertainty that expert elicitation reveals to be important but poorly represented within the analysis are high priority for communication with stakeholders [29].

Expert judgment studies do not reduce uncertainty; they merely quantify it. If the uncertainties are large, as indeed they often are, then decision makers cannot expect science to relieve them of the burden of deciding under conditions of ambiguity [52].
However, structured expert judgment can provide insights into the nature of the uncertainties associated with a specific risk and the importance of undertaking more detailed analyses to design meaningful strategies and policies for dealing with climate change in the spirit of deliberative thinking [52].

Table 6: Quant.2: Uncertainty Quantification via Expert Assessment

ID	Recommendation
Quant. 2.1	**Forecast Quality** **Recommendation:** Provide an indication of forecasters' confidence in the forecast quality **Rationale:** Non-specialist users may not want to receive detailed technical information. However, having an indication of forecasters' confidence regarding forecast quality may be valued by users. **Sources:** [20]
Quant. 2.2	**Scope relevant uncertainties.** **Recommendation:** Use expert elicitation and/or literature review to scope uncertainties **Rationale:** Expert elicitation or literature review can be used to scope a list of relevant uncertainties and to group them in pertinent ways (e.g. data and processes). **Sources:** [29]
Quant. 2.3	**Assess the consensus of expert elicitation.** **Measure and visualise consensus (or its lack) on uncertainties**. **Recommendation:** Scope a list of relevant uncertainties e.g. via expert elicitation and/or literature review, and use a formal process to investigate perceptions of those uncertainties in terms of their: **importance**: the believed potential to affect modelling results, **level of uncertainty**: from well understood (low) to little information (high), **representation**: the extent to which the analysis already accounts for the source of uncertainty. **Rationale:** Use a formal approach to assess the consensus of expert elicitation about uncertainties. Once perceptions of uncertainty are clarified and priorities are identified, a stakeholder communication plan can be developed. Three aspects of each source of uncertainty should be investigated: **Importance**: to do with how sensitive a model's results are to small changes in the source of uncertainty. **Representation**: the extent to which the analysis already accounts for the source of uncertainty.

	Level of uncertainty: ranging from low where a variable is well understood to high where there is little information or it is known to be highly uncertain. Sources of uncertainty that expert elicitation reveal to be important but poorly represented within the analysis are high priority for communication with stakeholders. Sources of uncertainty that are believed to have a small impact on analysis results and are well understood can probably be left out of wider conversations with stakeholders. A visualisation approach can be a useful tool to prioritise those uncertainties that need to be communicated with stakeholders. [Figure 11 on page 62 of Walton et al. (2024)] **Sources:** [29]
Quant. 2.4	**Consider goals when choosing expert elicitation method** **Recommendation:** Consider your goals when choosing a methodology for expert elicitation. **Rationale:** Different Structured Expert Elicitation approaches exist and care should be given to the goals before choosing whether an individual or group elicitation is most suitable. Individual elicitation methods avoid social influences and dominance effects but group elicitation can serve to highlight things that individuals may not have thought of alone. **Sources:** [51]
Quant. 2.5	**Individual Structured Expert Elicitation** **Recommendation:** Use individual elicitation methods such as the IDEA protocol to mitigate against dominance effects. **Rationale:** The reliability of expert judgement will always be sensitive to which experts participate and how questions are asked. However, structured protocols such as the IDEA protocol improve the quality of these judgements by taking advantage of the wisdom of the crowd whilst mitigating a range of the most pervasive and potent sources of bias. **Investigate**: All experts individually answer questions, and provide reasons for their judgements **Discuss**: Experts are shown anonymous answers from each participant and a visual summary of responses **Estimate**: All experts make second final and private estimate **Aggregate**: The mean of experts' second round responses are calculated In the IDEA protocol, the purpose of the discussion step is not to reach consensus but to resolve ambiguity, promote critical thinking and to share evidence. **Sources:** [49]

Decision support

The main drivers of climate change (which include economic development and population growth) are inherently uncertain, especially at the longer term, and are best explored using a scenario approach. At a detailed level, our understanding of the Earth system is incomplete which may give rise to surprises, unforeseen effects and unanticipated impacts (sometimes referred to as 'ignorance'). Therefore decision-making frameworks are needed that can cope with scenario uncertainty and ignorance.

Uncertainty is its own kind of information, and it can be useful for making better decisions. Decisions that make sense across a range of possible futures are more robust. Areas of uncertainty can be areas where parties with different interests or perspectives can find space for mutually acceptable solutions. By embracing uncertainty, we remind ourselves that the future is still open, and long-term climate outcomes can still be fundamentally shaped by the choices we make today. [29]

Table 7: Quant.3: Uncertainty Quantification for Decision Support

ID	Recommendation
Quant. 3.1	**Work backwards from the decision point** **Recommendation:** Use the decision point to identify relevant uncertainties. **Rationale:** Strengthen decision-making by working backwards from a particular decision point or vulnerability to identify the uncertainties that need to be quantified. Combine climate change information with other relevant factors. **Sources:** [35] [Comm.1.20]
Quant. 3.2	**Identify and characterise sources of uncertainty** **Recommendation:** Characterise the sources of uncertainty and assess their magnitude. **Rationale:** This is likely to result in a long list of uncertainty sources and could be approached by analysing each step of the assessment process by considering where in the assessment different types of uncertainty may occur. **Sources:** [1],[38]
Quant. 3.3	**Assess sources of uncertainty.** **Recommendation:** Assess the magnitude and relevance of the sources of uncertainty. **Rationale:** Assess the relative importance of each source of uncertainty by its impact on the final decision or outcome. This could be done by performing a sensitivity analysis or be based on expert judgement. The nature of the uncertainty will inform the quantification strategy. **Sources:** [1],[38]
Quant. 3.4	**Characterise key uncertainties** **Recommendation:** Characterise key uncertainties in detail **Rationale:** Key uncertainties, identified by their impact on the final decision, or their relevance to key vulnerabilities or thresholds, should be analysed and characterised in

	detail. **Sources:** [1],[38]
Quant. 3.5	**Re-evaluate uncertainties** **Recommendation:** Review uncertainty assessments and re-evaluate **Rationale:** Uncertainties may need to be re-evaluated throughout the assessment process, as it may not be possible to identify, prioritise and characterise all sources of uncertainty at the start. **Sources:** [1],[38]
Quant. 3.6	**Contextualise information.** **Recommendation:** Provide context for the uncertainty information. **Rationale:** Uncertainties need not only to be analysed and described but also communicated. Provide decision makers with an understanding of the context of the information that is given to them whilst taking care not to overload them. The information needs to be sufficient to use and not mis-use the data product. To limit the overload potential it can be useful to have a range of methods with which to communicate uncertainty and then to use those methods that are most relevant to the decision situation. **Sources:** [1],[38]
Quant. 3.7	**Match the quantification method to the level of uncertainty** **Recommendation:** The quantification method will depend on the level of uncertainty. **Rationale:** The taxonomy of levels of uncertainty ranges from well-characterised to total ignorance. The level of uncertainty should determine the type of information that is provided to inform decisions. Well characterised uncertainty can be quantified with probabilities. However, if deep uncertainty dominates, employ scenario planning and consider whether a reasonable worst case scenario, or a low likelihood - high impact scenario is appropriate. **Sources:** [46]
Quant. 3.8	**Decision making under deep uncertainty** **Recommendation:** Use a decision-making framework that can cope with scenario uncertainty and ignorance. **Rationale:** Decision Making under Deep Uncertainty (DMDU) is a set of concepts, methods, and tools to inform decisions when there exist substantial and significant limitations on what is and can be known about policy-relevant questions. DMDU practice is an analytical framework that evaluates potential solutions across multiple plausible future scenarios rather than attempting to predict a single future outcome. The Intergovernmental Panel on Climate Change (IPCC) uses DMDU to explore key concepts such as risk, scenarios, treatment of uncertainty, storylines and high-impact, low-likelihood outcomes, and both adaptation and climate resilient development pathways. **Sources:** [46, 81]

Observational data and reanalysis

This section presents recommendations for the use of observational data, including point-measurements from weather stations, gridded observational datasets and reanalysis products. High-quality observational records are the foundation upon which climate models are calibrated and validated. However, while these datasets are often taken at face value, they are subject to inherent uncertainties. The following recommendations are designed to help users navigate these uncertainties when selecting and applying observational data in their workflows.

Table 8: Quant.4: Uncertainty Quantification for Observational Data and Reanalysis

ID	Recommendation / Insights
Quant. 4.1	**Be aware that observations have uncertainties** **Recommendation**: The uncertainty associated with observational data should not be disregarded. If, for operational reasons, a simplification should be made, this decision should be clearly documented and communicated. **Rationale:** Uncertainty is inherently linked to any measurement. In fact, some institutions like WMO define the uncertainty requirements that observations from instruments should follow. Importantly and as stated in WMO-No.8 Volume I, these requirements are sometimes only met with the highest quality equipment and procedures, which are not available ubiquitously.
Quant. 4.2	**The data we collect from the real world is subject to errors and approximations** **Recommendation**: The whole processing chain (lineage) should be documented. **Rationale**: The uncertainty inherent in climate observations arises from a multi-layered process: • **Measurement Uncertainty** This is the error inherent in the measurement device itself. For example, a thermometer might have a calibration drift, or a rain gauge might "under-catch" water during high winds. Satellites don't measure temperature directly; they measure radiance. The conversion of energy into a temperature value involves complex algorithms that introduce their own noise. • **Processing Uncertainty** Raw data is rarely "clean". To see long-term trends, scientists must perform homogenization. For example, if a weather station was moved from a grassy field to a paved parking lot in 1990, the temperature would jump. In that case, the jump needs to be mathematically corrected. Different homogenization methods yield slightly different historical records. • **Structural/Spatial Uncertainty** Climate services usually need a "map" (a grid), but observations are very rarely directly gridded, for example weather stations are scattered points with gaps in between. To fill the gaps (e.g., over a mountain range with no sensors), statistical models or "reanalysis" are used. Each model creates a different estimation of what is happening in those empty spaces.
Quant. 4.3	**The scope and limitations of uncertainty coming from observations should be transparent and understandable**

	Recommendation: Even though the full traceability and reproducibility of the uncertainty estimation may only be comprehensible to experts, in order to avoid the misuse of uncertainty, providers should ensure that the limitations, scope and purpose of the uncertainty estimate are acknowledged and well-understood by users. This information should be easily findable and accessible through a Permanent Identifier always attached to the metadata and other relevant locations. **Rationale:** Observational datasets represent a big field with very different levels of processing. The intricacies of the calibration/validation processes, the methodologies used to estimate uncertainty, and their limitations are frequently only understandable by experts. The uncertainty estimation for complex observational products like reanalysis (see limitations of ERA5), gridded observational datasets from stations (see limitations of ECA&D) or even Automatic Weather Stations is not trivial.
Quant. 4.4	**Multiple observational datasets exist: explore them when available** **Recommendation:** When available, use multiple observational sources, as there might be differences between them. It's highly recommended to analyse if these sources are consistent with each other. For example, by checking if their values lie within each other's uncertainties. **Rationale:** Usually many observational datasets that monitor the same climate variable are available. These datasets may have been processed by different institutions, or even created from the observations coming from different instruments.
Quant. 4.5	**The Observation-Model Relationship** **Recommendation**: Observations and models should be treated as complementary tools. **Rationale:** The assumption that observations are inherently superior to model outputs is a common misconception in climate services. In reality, both are representations of the same physical system, each with its own strengths and limitations. While models are often criticized for their reliance on parameterizations and physical approximations, observations are frequently constrained by sampling bias and instrumental limitations. Furthermore, the comparison between the two is rarely "apples-to-apples." A weather station measures a single point in space (a point measurement), while a climate model represents the average state of a large grid box (an area-average). This "representativeness error" means that even a "perfect" model and a "perfect" sensor will naturally disagree because they are measuring different spatial scales.

Climate Extremes

Key climate risks are often (though not always) associated with the occurrence of extreme events. At the same time, extremes present specific challenges for uncertainty quantification and communication. By definition they occur infrequently, which typically limits the available sample size for estimating their characteristics, evaluating model performance, and detecting change. As a result, uncertainty in extremes is often larger, more sensitive to methodological choices, and more difficult to constrain than for mean conditions or more common events. The following recommendations highlight good practice for defining, analysing, and communicating climate extremes.

Table 9: Quant.5: Uncertainty Quantification for Climate Extremes

ID	Recommendation
Quant. 5.1	**What is an extreme event?** **Recommendation:** Be clear about what constitutes an extreme event **Rationale:** There is no standard definition of when an event can be considered extreme. Some studies will focus on the lower or upper end of the statistical distribution of a climate variable (e.g., the 95th or 99th percentile of rainfall which - depending on the exact definition - may be expected to be exceeded every year), but these may not correspond with the user's perception of an extreme event. It is essential to clarify with the user how extremes are defined and which indicators best capture relevant impacts. Ideally, the defined extremes and indicators should be consistent with sectoral thresholds, operational triggers or other impact-based criteria. **Sources:** [1]
Quant. 5.2	**Use appropriate statistical techniques for extremes** **Recommendation:** Use appropriate statistical techniques to estimate the frequency or probability of extreme events **Rationale:** Especially high-impact extreme events to which society is not well adapted or prepared are usually very rare. This means their sample size can be very small or even non-existent, even in model simulations. Specialised statistical techniques exist to allow for a more robust estimation of these extremes, including the associated uncertainties in the estimate, than would be possible from direct empirical frequency estimates based on limited samples alone. Communicating the uncertainty in the estimate is essential, as estimates of these extreme quantiles are increasingly uncertain at more extreme levels, especially if the return period exceeds the length of the data record. Also the robustness of the results against the choice of the extreme value distribution and the inclusion of additional parameters should ideally be evaluated. **Sources:** [1]
Quant. 5.3	**Use appropriate data and methods** **Recommendation:** Select appropriate data sources and methodologies for the analysis of extreme events **Rationale:** Compared to other data sources, climate model ensembles and in particular large initial-condition ensembles and millennial-scale climate simulations provide an opportunity to estimate the role of natural variability in extreme-event probability giving more robust estimates. In a similar way, large ensembles of past seasonal or decadal forecast or hindcast data may allow the identification of plausible—but previously unseen—extreme weather events by generating multiple physically consistent realisations of historical conditions, thereby increasing the sample of possible outcomes beyond the single observed trajectory. If the sample of extreme events is too small and/or too much affected by natural variability, a more robust signal of changes in extremes may sometimes be obtained by aggregating over larger regions. **Sources:** [1]
Quant. 5.4	**Beware of additional uncertainty** **Recommendation:** Evaluate additional sources of uncertainty and data limitations

	Rationale: When analysing rare and/or high-impact extreme events, additional sources of uncertainty and data limitations may arise due to a very small sample size, non-stationarity and inhomogeneities in the data record, and a reduced measurement reliability. Where feasible, these additional uncertainties should be evaluated and/or transparently documented. **Sources:** [1]
Quant. 5.5	**Confusing terminology and concepts** **Recommendation:** Avoid confusing terminology such as "a once-in-a-100-years event" **Rationale:** A common source of misunderstanding relates to the concept of return periods, as reflected in phrases such as "a once-in-a-100-years" or "100-year event". Statistically, such an event has an annual probability of exceedance of 1%, which applies every year regardless of whether a similar event has recently occurred. Many people interpret this as an event that happens exactly once every 100 years, leading to misconceptions such as assuming it is less likely after it has occurred or more likely after a long absence. Such misinterpretations can distort risk perception and negatively affect decision-making. To avoid confusion, it may be more effective to communicate likelihood in terms of annual exceedance probability, the expected number of events over a relevant period (e.g., the lifetime of infrastructure), or through risk-based storylines. **Sources:** [1]
Quant. 5.6	**Use storylines** **Recommendation:** Create storylines or narratives of compound or cascading extreme events and risks **Rationale:** Storylines are effective for considering risks from compound extreme events, namely those where severe impacts are triggered by the interaction of more than one variable. Neither variable itself needs to be very extreme but the combination can result in severe impacts. Storylines can be used to define very complex events, in a flexible way, starting from the impacts. **Sources:** [1, 35]

Sub-seasonal, seasonal and annual forecasting

Seasonal climate prediction provides information on climate conditions in the coming months up to a year ahead, and can support preparedness and risk management across many sectors. However, the level of predictability at these timescales is often limited and varies strongly with variable, region, season, lead time, and the prevailing climate state. Uncertainty is therefore an essential component of seasonal forecast products. Compared with climate services that focus at other time scales, seasonal prediction must explicitly account for uncertainties arising from initial and boundary conditions, model structure, and internal climate variability, while demonstrating that forecasts provide information beyond climatology. The following recommendations outline good practice for assessing, quantifying, and communicating these uncertainties in a way that enables users to understand both the potential value of the forecast and its limitations.

Table 10: Quant.6: Uncertainty Quantification for Sub-seasonal, Seasonal and Annual Forecasting

ID	Recommendation
Quant. 6.1	**Communicate skill** **Recommendation:** Communicate skill information together with the forecast **Rationale:** Forecast skill determines the extent to which climate predictions provide useful and actionable information, beyond just climatology. The skill of a forecast is not constant but highly dependent on lead time, region and variable of interest; it may also be conditional on a particular climate state such as an ENSO phase. Information about the skill is essential for users in order to distinguish between informative forecasts and forecasts with limited predictive value. The skill of climate forecasts can be evaluated using a range of well-established metrics. Reliability information in particular helps users to understand whether the stated probabilities can be interpreted at face value, which is essential for risk-based decision making. In addition to the skill, also the calculation method and its assumptions and limitations should be communicated transparently. **Sources:** [79]
Quant. 6.2	**Be transparent about low skill** **Recommendation:** Be transparent about low skill and limits to predictability, with the provision of climatological information as an alternative or reference **Insight/rationale:** Forecast skill in seasonal-to-decadal prediction can vary markedly by region, variable, season, lead time, and prevailing climate conditions, and in some situations predictive capability may be weak or absent. In such cases, model-based forecasts may not provide information beyond what is available from historical climate statistics. Explicitly communicating low skill helps manage expectations and reduces the risk of over-interpretation. Presenting climatology or simple benchmarks offers users a transparent baseline against which the added value of the forecast can be judged. **Sources:** [20]
Quant. 6.3	**Use hindcasts** **Recommendation:** Interpret and communicate climate forecasts in the context of the corresponding hindcasts of the same modelling system **Rationale:** Hindcasts provide the primary reference for assessing model biases, variability, and forecast skill at specific lead times. Expressing climate predictions as anomalies relative to the model's own climatology reduces the influence of systematic errors and supports consistent interpretation across time, space, and variables. This approach enables meaningful comparison with historical performance and helps users distinguish predictable signals from model artefacts. Expressing results as anomalies relative to each model's climatology also allows for a comparison across different modelling systems and the creation of multi-model forecasts. **Sources:** [80]
Quant. 6.4	**Use multi-model forecasts** **Recommendation:** Use a multi-model ensemble seasonal forecast **Insight/rationale:** Individual prediction systems exhibit structural biases and different representations of key processes, which can strongly influence forecast outcomes.

	Combining multiple models generally provides more robust estimates of the uncertainty and often improves reliability and skill compared with single-model forecasts. Ideally, single-model results are presented only within the context of the broader multi-model ensemble. **Sources:** [80]
Quant. 6.5	**Use probabilities** **Recommendation:** Express seasonal forecast information probabilistically wherever appropriate, based on user-relevant thresholds to ensure practical relevance **Insight/rationale:** As seasonal prediction systems are usually ensemble-based, the results are ideally expressed probabilistically. Probabilistic information better represents forecast uncertainty and supports risk-based decision-making. Forecasts for the exceedance of user-defined thresholds may be more useful than forecasts for conditions being above/below average. Indeed, likelihoods within 40%–60% for above/below average conditions have been shown to offer little useful information. Wherever scientifically appropriate, providers should work with users to identify decision-relevant thresholds and explore whether providing information about the likelihood of exceedance of those thresholds is feasible. **Sources:** [20]
Quant. 6.6	**Assist users** **Recommendation:** Help users understand and interpret probabilistic forecasts **Insight/rationale:** Probabilistic forecasts can be unintuitive, and users may misinterpret categories or percentages as deterministic statements. Supporting understanding through e.g., examples or simple games to understand tercile categories, helps ensure that probabilities are used appropriately in decision-making and reduces the risk of overconfidence or misuse. **Sources:** [19, 36, 61, 62]

Decadal (intersection between annual and projections)

Decadal predictions aim to provide information about the evolution of the climate system over the coming years up to a decade ahead, combining the influence of the current climate state with externally forced change. Many of the principles and recommendations for seasonal prediction are also relevant to decadal prediction, particularly those related to multi-model ensembles, skill assessment, probabilistic communication, and transparency about limitations. However, decadal prediction introduces additional challenges that warrant specific guidance. At these lead times, the relative roles of internal variability and long-term climate forcing become intertwined, assumptions about future external drivers become more important, and model drift and changing background climatology may complicate the interpretation. The following recommendations address these aspects.

Table 11: Quant.7: Uncertainty Quantification for Decadal Prediction

ID	Recommendation
Quant. 7.1	**Distinguish between variability and trend** **Recommendation:** Where feasible, distinguish between the contributions from internal climate variability and externally forced trends. **Insight/rationale:** At decadal lead times, climate predictions reflect a combination of variability arising from the initial climate state, natural climate variability (including unpredictable events such as volcanic eruptions), and longer-term trends driven by greenhouse gas emissions and other external forcings. Users may need to know to what extent the forecast is influenced by these components, in order to avoid misinterpretation. Approaches such as the use of large ensembles, comparison of initialized and uninitialized simulations, detection and attribution techniques, or other statistical methods can help to separate these components. Where appropriate, the methods used to make this distinction should be documented and may need to be communicated to the user as well. **Sources:** [82,83]
Quant. 7.2	**Communicate assumptions** **Recommendation:** Evaluate and communicate the implications of external forcing assumptions on the decadal forecast. **Insight/rationale:** Unlike seasonal forecasts, decadal predictions are increasingly sensitive to assumptions about future external drivers of the climate system such as greenhouse gas concentrations, aerosols, land use, or volcanic activity. Some of these assumptions may or may not materialise, and the forcings could develop differently from what is assumed in the forecast. This could have a substantial impact on the forecast outcomes. Transparent communication of the assumptions being made and the potential impact on the prediction helps users understand what aspects of the prediction are conditional and how confidence may evolve with lead time. Sensitivity experiments, alternative forcing pathways, or explicit statements regarding unpredictable drivers such as volcanic eruptions can help illustrate this conditionality. **Sources:** [84]
Quant. 7.3	**Account for model drift** **Recommendation:** Evaluate and/or quantify the influence of model drift on seasonal predictions and communicate its impacts to the users. **Insight/rationale:** Following initialization, coupled climate models typically adjust toward their preferred climatological state, producing systematic changes that can persist for several years. At decadal lead times, this drift can be comparable in magnitude to the predicted signal and affect the interpretation of trends and anomalies. While seasonal forecasts also require bias correction, drift in decadal predictions is more pronounced, lead-time dependent, and often less well constrained by available hindcasts. What is more, postprocessing methods that are used to correct for model drift may also introduce additional uncertainty. **Sources:** [82]
Quant. 7.4	**Account for trends**

	Recommendation: Account for externally forced climate trends present in both the reference climatology and the forecast period when estimating anomalies, probabilities, and thresholds. **Insight/rationale:** At decadal lead times, the externally forced changes in the climate system can modify the climatology not only in the reference period but also within the prediction horizon itself. As a result, quantities such as anomalies, exceedance probabilities, and return periods depend on how the evolving baseline is treated. While similar considerations may arise in seasonal forecasting, their influence is usually much smaller. Depending on the region, time period and variable of interest, it may be necessary to account for the forced trend in the estimation, for example by applying detrending techniques to avoid potentially biased or misleading outcomes. **Sources:** [82]

Climate Projections

Climate projections are used to explore the development of the climate system at longer timescales. Greenhouse gas (GHG) emissions mainly originate from the use and transformation of energy, agriculture, land use (change) and industrial activities. The future development of these sources is influenced by trends in socio-economic development, including population, economic activity, technology, politics, lifestyles and climate policy. (AR6 WG3 Ch3).

A Scenario is a description of how a future may develop, it is based on a coherent and internally consistent set of assumptions about the key drivers of socio-economic development. Scenarios are not predictions, instead they provide a 'what-if' investigation of the implications of various developments and actions (AR6 WG1 Ch1, Moss et al., 2010).

Understanding the effects of scenarios on the climate involves modelling the Earth's response to changes in GHG emissions/concentrations and regional climate forcing. The output of climate model simulations that are forced with these scenario inputs are known as climate projections. Different scenarios will result in a different evolution of the climate system when used as input into a climate model (scenario uncertainty). But at the same time, different climate models will yield different projections from the same scenario (model uncertainty).

Model intercomparison studies generate sets of projections termed 'multi-model ensembles' (AR5 WG3 Ch2). Ensembles of model runs generated by different models convey the scatter of the climate response and natural internal climate variability around the scenarios as sampled by a set of models (AR5 WG3 Ch3). At longer timescales, the ensemble uncertainty of climate projections is dominated by model uncertainty and scenario uncertainty (75).

Table 12: Quant.8: Uncertainty Quantification for Climate Projections

ID	Recommendation
Quant. 8.1	**Consider multiple climate scenarios** **Recommendation:** • Consider multiple scenarios for analyses that need to take into account the uncertain changing climate. • There may be cases where looking at a single scenario (e.g. a worst-case scenario) is justified. However, in principle, no likelihood is attached to any individual scenario. **Rationale:** Analysts often forget that scenarios are illustrative possible futures along a continuum. They tend to make use of those scenarios in a deterministic fashion without recognising that each individual scenario has an equal probability of occurrence and is only one of many possible outcomes (AR5 WG3 Ch2). It is therefore good practice to consider multiple scenarios for analyses that need to take into account the uncertain changing climate. Example scenarios: • Climate modelling groups participating in CMIP6 (Coupled Model Intercomparison Project phase six) that informed the IPCC sixth assessment cycle (AR6) were asked to run simulations for the following scenarios: ◦ **SSP1-2.6** for sustainable climate pathways, ◦ **SSP2-4.5** for middle-of-the-road, ◦ **SSP3-7.0** for regional rivalry, and ◦ **SSP5-8.5** for fossil fuel-rich development. ◦ **SSP1-1.9** for the 1.5°C Paris Agreement goal was also requested (AR6 WGI Ch4). • KNMI'23 climate scenarios for the Netherlands were constructed to primarily explore water security and water safety. The KNMI'23 analysis explored wet and dry climate projections from a high climate forcing scenario and a low climate forcing scenario: ◦ Low-dry, Low-wet ◦ High-dry, High-wet There may be cases where looking at a single scenario (e.g. a worst-case scenario) is justified. However, in principle, no likelihood is attached to any individual scenario. A particular scenario can sometimes be discarded if it is considered to be implausible or unrealistic. For example CMIP7 will not use the SSP5-8.5 (fossil fuel-rich development) scenario because it is considered to be too implausible to unfold (53). **Sources:** [1, 52, 46, 34]
Quant. 8.2	**Use multi-model ensembles and/or perturbed physics ensembles to evaluate climate model uncertainty**

	Recommendation: Explore model uncertainty by using simulations from multiple models and/or multiple simulations from the same model with perturbations to key, uncertain physical parameters. **Rationale:** As well as considering multiple scenarios it is recommended to use simulations from multiple models in order to explore model uncertainty. Different climate models encode the physics of the Earth system in different ways and are run within different computational environments. Model uncertainty covers two uncertainty situations: 1. Different climate models will yield different climate projections from the same scenario. 2. The same climate model could yield different climate projections for the same scenario if key internal parameters are changed. Multi-model ensembles are used to characterise the first kind of model uncertainty which arises because different models use different code bases and computational environments. Perturbed Physics Ensembles (PPEs) systematically vary (perturb) key, uncertain physical parameters within a model, such as those related to atmospheric convection, cloud formation, and ocean mixing. Model uncertainty of climate model projections is characterised by some measure of spread across an ensemble of simulations for a scenario. The most common approach is to calculate the arithmetic mean of the individual model results, referred to as an unweighted multi-model mean. The uncertainty of the ensemble is then represented by the 5%-95% range of the multi-model mean. This approach of "one vote per model" gives equal weight to each climate model regardless of (1) how many simulations each model has contributed, (2) how interdependent the models are or (3) how well each model has fared in objective evaluation. **Sources:** [1]
Quant. 8.3	**Multi-model ensemble members should not be treated as purely independent** **Recommendation:** Account for model inter-dependence in statistical analyses of model ensembles **Rationale:** Multi-model ensembles (MMEs) are constructed from climate model simulations from multiple climate modelling centres. However some climate models have been developed by sharing model components (e.g. land surface model) leading to shared biases. Thus, MME members cannot be treated as purely independent in a statistical sense. Model interdependence should be accounted for when calculating multi-model ensemble statistics. A probabilistic assessment of the ensemble should account for

	model biases, model interdependence, and knowledge of how the ensemble was constructed. If this is not possible then the assumption of model independence should be recorded. **Sources:** [54]
Quant 8.4	**Consider the use of model weighting schemes** **Recommendation**: Consider using a weighting scheme for multi-model ensemble analysis. Conclusions drawn from ensembles should at least test their sensitivity to how the models in the ensemble are selected. **Rationale:** The goal for a multi-model ensemble should be to maximize diversity in models yet ensure good performance for all members, and minimize inter-dependency. In principle, this could be achieved with a sufficiently large and broad ensemble to start with, and an appropriate weighting that takes into account two distinct factors: performance metrics measuring model skill, and the inter-dependence with other models in the ensemble. Conclusions drawn from ensembles should at least test the sensitivity to how the models in the ensemble are selected. **Sources:** [1, 54]

Regional Analysis (Downscaling & Bias Correction)

Regional analysis stems from the need to resolve Global Climate Models (GCMs) at a higher spatial resolution than their standard output—typically 1° in longitude and latitude—and to align these models with ground-based observations.

This field has become a high-priority research frontier, driven by the increasing visibility of climate change impacts at regional scales and the recent surge in computational power. Furthermore, the rapid advancement of AI is opening new avenues for sophisticated downscaling techniques. In the climate services market, downscaling and bias correction represent a primary value proposition for the private sector, as they bridge the gap between raw global data and the customized, actionable insights required by end-users.

The recommendations presented here are based both on the expertise of the authors and the content provided by Rampal et al. 2024 [76].

Table 13: Quant.9: Uncertainty Quantification for Regional Analysis

ID	Recommendations
Quant. 9.1	**Providers must test and disclose how their algorithms perform "out of distribution"** **Recommendation**: Providers must test and disclose how their algorithms perform "out of distribution". Users should be cautious when applying downscaled data to extreme "worst-case" future scenarios or simply climatic conditions that the model hasn't seen

	in its training phase. **Rationale**: Statistical models are often trained on historical observations, but the future climate may look fundamentally different.
Quant. 9.2	**Providers should aim towards using interpretability tools to show which Global Climate Model features are driving local results** **Recommendation**: Providers should aim towards using interpretability tools to show which Global Climate Model features are driving local results, helping users build physical trust in the statistical output. More generally it may be a good idea to compare the results (patterns, trends) with that of the parent climate model. If a statistical downscaling model produces a different trend from the original model (e.g., getting drier instead of wetter), the statistical model should be questioned. **Rationale**: Deep learning models are notoriously difficult to decipher, making it hard to see how they reach a specific climate conclusion. More generally, it may be hard to assign a physical interpretation to any statistical downscaling or bias correction model.
Quant. 9.3	**Don't assume statistics or AI "fixes" bad science by default.** **Recommendation**: Don't assume statistics or AI "fixes" bad science by default. Users should ask for the validation metrics of the original RCM; if the physical model has a bias in precipitation, the fast statistical version will likely carry that same error, unless specific techniques are applied to solve this issue. **Rationale**: A statistical emulator is only as good as the Regional Climate Model (RCM) it mimics.
Quant. 9.4	**Users need to be aware that a single downscaled member represents just one "roll of the dice"** **Recommendation**: Providers could use Artificial Intelligence's speed to downscale larger initial-condition ensembles. Users need to be aware that a single downscaled member represents just one "roll of the dice" and may not capture the full range of natural climate swings. **Rationale**: Most downscaling approaches like the Coordinated Regional Climate Downscaling Experiment (CORDEX) use only one initial condition per Global Climate Model (GCM), ignoring internal climate variability.
Quant. 9.5	**Before investing in high-resolution data, users should ask for "added value" metrics** **Recommendation**: Before investing in high-resolution data, users should ask for "added value" metrics. Providers should clearly demonstrate where the downscaling significantly improves upon the global model rather than just adding "visual noise." **Rationale**: Regional Climate Models are assumed to be better than Global Climate Models, but they don't always add significant value for every variable.
Quant. 9.6	**Providers should be transparent about which physical "shortcuts" (parameterizations) are being used** **Recommendation**: Providers should be transparent about which physical "shortcuts" (parameterizations) are being used at the kilometer scale. Users should be wary of high-resolution products that don't account for updated microphysics or convection. **Rationale**: High-resolution models (1–4 km) often still use physics formulas designed for 100 km grid boxes.

Quant. 9.7	**Massive Ensembles for Rare Events** **Recommendation**:Statistical emulators could be used to bridge the gap. While dynamical models provide the physically plausible simulation of the evolution of the climate system, statistical models can generate the thousands of simulations needed to create a statistically robust probability curve for extreme events. **Rationale**: Properly estimating the risk of a "once-in-a-century" flood requires a massive number of model runs.
Quant. 9.8	**The Local Feedback Loop** **Recommendation**: For infrastructure projects in complex terrain, prioritize Convection-Permitting RCMs (CP-RCMs) or their emulators. These are essential for capturing the "ground truth" of flash floods and hailstorms that global models are too coarse to see. **Rationale**: Regional Climate Models (RCM) can capture unique local signals (like mountain effects or coastal breezes) that Global Climate Models (GCM) miss entirely.
Quant. 9.9	**Balance Speed with Physical Rigor through Hybrid Approaches** **Recommendation**: Use a hybrid approach. Providers should use dynamical models to establish a physical "anchor" and statistical models to explore the uncertainty space around it. Users should look for services that combine the two rather than relying on pure statistical "magic." **Rationale**: Statistical models allow for rapid downscaling, but dynamical Regional Climate Models (RCM) provide the underlying physical consistency.
Quant. 9.10	**Document the Methodology Chain** **Recommendation**: Demand understandable data provenance. Providers should offer a clear map of every processing step, and evaluate the uncertainty not just at the final output, but as a cumulative result of the entire chain. **Rationale**: Uncertainty builds up at every step—from the GCM choice to the downscaling algorithm to the final bias correction.

Metadata for uncertainty information

Metadata is 'information that helps the user assess the usefulness of a dataset relative to their problem'. The importance of appropriate metadata reporting increases as growing numbers of users with varying degrees of experience find they need to use climate data.

In the context of modelling for decision support there is no fixed method for recording uncertainty however there is consensus about the information that should be included in an uncertainty assessment. Model uncertainty analysis frameworks that classify uncertainty can be used to identify the critical uncertainties which must be communicated if the model output is to be used to support decision making.

In the context of uncertainty assessments of observation data the metadata should allow the user to determine data quality and fitness for their analysis or data. Assessing data fitness or suitability

involves understanding data limitations (such as mismatches between user and data concepts) and quantifying the direction and magnitude of the uncertainties.

Each step in the value chain from observations and measurements to modelling at various scales represents a different community of practice, so uncertainty information may need to be understood by actors that are far removed from the original work. Metadata ontologies provide a potential framework for maintaining a shared understanding of uncertainty.

Table 14: Quant.10: Metadata for Uncertainty Quantification

ID	Recommendation
Quant. 10.1	**Report uncertainty in a transparent format** **Recommendation:** Report on each source of uncertainty **Rationale:** Present each source of information, whether climate model output, palaeoclimatic data, observations or expert elicitation in a transparent and auditable format that is open to challenge and revision as scientific understanding grows. **Sources:** [35]
Quant. 10.2	**Classify and Communicate Uncertainty** **Recommendation:** Describe uncertainty using a structured framework to provide clarity for both the producers and the consumers of uncertainty information. **Rationale:** Walker et al. (2010) have developed a conceptual framework for the systematic treatment of uncertainty in model-based decision support. Understanding the various dimensions of uncertainty improves communication among analysts as well as between them and policymakers and stakeholders so that critical uncertainties can be identified, articulated, and prioritised. Describing uncertainty using a structural framework provides clarity for both the producers and the consumers of uncertainty information. A three dimensional typology for uncertainty classification • The **location** of uncertainty - where the uncertainty manifests itself within the model complex • The **level** of uncertainty - Where the uncertainty manifests itself along the spectrum between deterministic knowledge and total ignorance • The **nature** of the uncertainty - Whether the uncertainty is due to the imperfection of our knowledge or is due to the inherent variability of the phenomena being described. The location of uncertainty is about: • Context uncertainty- The choice of the boundaries of the system to be modelled and the framing of the issues to be modelled. • Model uncertainty - Which arises both from an incomplete understanding of the system and from the computer implementation of the model.

	• Input uncertainty - To do with external driving forces that produce changes within the system (e.g. scenario variables) and internal system data (e.g. land use maps). • Parameter uncertainty - To do with the data and methods used to calibrate the model parameters (constants in the model that are unchanging for the chosen scenario). • Model outcome uncertainty - The accumulated uncertainty caused by the uncertainties in all of the above locations (context, model, inputs, parameters) that are propagated through the model. Bree and Van der Sluijs (2014) expand the three-dimension model further to also include • **qualification of knowledge base -** The reliability of the information used, the degree to which the established results and statements are underpinned (i.e. evidence-based). • **value-ladenness of choices** - The extent to which the implicit and explicit choices made in the assessment are value-laden and/or subjective. If the 'value- ladenness' is high for any part of the assessment, then it is imperative to analyse whether this could lead to an arbitrariness, ambiguity or uncertainty of the policy relevant conclusions. **Sources:** [1, 70, 71]
Quant. 10.3	**Measurement Uncertainty instead of Measurement Error** **Recommendation:** Measurement uncertainty and measurement error are different and should not be used interchangeably. **Rationale:** • Measurement uncertainty is the doubt about the true value of the quantity that is being measured which remains after making a measurement. • Measurement error is the difference between the true value of the quantity and that of the measurement. • Measurement Uncertainty and Measurement Error are different and should not be used interchangeably. • For the CF-Conventions, the use of the standard uncertainty instead of standard error is considered to be best practice (although standard error is often included in uncertainty metadata for backwards compatibility). **Sources:** [66, 67]

Quant. 10.4	**Use ancillary variables to describe uncertainty**
	Recommendation: Use ancillary metadata variables to describe uncertainty.
	Rationale:
	• For physical measurements there is a standardised approach to characterising uncertainty, based around five properties of measurement uncertainty:
	  ○ Uncertainty interval - e.g. the standard deviation
	  ○ Uncertainty error type - e.g. random
	  ○ Uncertainty distribution - e.g. Gaussian
	  ○ Uncertainty evaluation - e.g. subjective
	  ○ Uncertainty correlation - e.g. random

	The Obs4MIPs project recommends the use of the following ancillary metadata to describe uncertainty: • Number of observations (nobs) The number of discrete observations or measurements from which a data value has been derived. • Uncertainty due to independent effects (uind) The per-datum component of uncertainty that is associated with uncorrelated effects, provided at one standard deviation. • Uncertainty due to structured effects (ustr) The per-datum component of uncertainty that is structured and correlated over a defined space/time scale, provided at one standard deviation. This correlation length scale in space and time must be provided in the variable metadata. • Uncertainty due to common effects (ucom) The per-datum component of uncertainty that is common to all observations of a given type (specific instrument, resolution, variable type) at one standard deviation. • Standard uncertainty (ustd) The per-datum standard uncertainty is a combination of independent (uind), structured (ustr) and common effects (ucom) and is equal to the positive square root of the sum of the components. The standard uncertainty is provided at one standard deviation. • For observations with asymmetrical uncertainty distributions, the standard uncertainty (ustd) can instead be replaced by providing upper and lower bounds for the uncertainty interval (lbnd) and (ubnd). **Sources:** [66, 67]
Quant. 10.5	**Propagate the uncertainty of the analysis** **Recommendation:** Uncertainty should be propagated through the steps of statistical analyses **Rationale:** The propagation of uncertainty is about how the uncertainty of the input data combines to produce uncertainty in the analysis results. For measurements there are online tools such as the UK National Physics Laboratory CoMET Toolkit which can handle, process, and store measurement data uncertainties and error-correlation information. https://www.comet-toolkit.org/about/ **Sources:** [69]
Quant. 10.6	**Maintain uncertainty information through the value chain** **Recommendation:** Maintain a record of uncertainty information that can be passed through the measurement and modelling value chain. **Rationale:** Each step in the measurement and modelling value chain represents a different community of practice, so uncertainty information may need to be understood by actors that are far removed from the original work. Metadata ontologies such as the Simple Standard for Sharing Ontological Mappings (SSSOM) (Matentzoglu et al. 2022) provide a potential framework for maintaining a

	shared understanding of uncertainty information throughout the value chain. **Sources:** [72]
Quant. 10.7	**Record assumptions as a caveat to the results of a report** **Recommendation:** Record assumptions as a caveat to the "results" of a report or research project to help future data users to assess the applicability of the data to their own purposes. **Rationale:** • Users of observation data have to be pragmatic and use the data that is available, despite the fact that the existing data was (usually) collected for a different purpose to the one they wish to use it for. • Metadata alone does not communicate the data producer's model of the world embedded in data. • The consequences and uncertainties of unknown mismatches between the (remotely held) data objects and those of the user can be far more profound than those described within uncertainty metadata. • Recording assumptions as a caveat to the "results" of a report or research project, will help future data users to assess the applicability of the data to their own purposes. **Sources:** [68]

Deep Uncertainty

Deep uncertainty can be challenging to communicate and is typically not well understood by decision makers, even those who are risk-literate [29].
Deep uncertainty is itself an ambiguous term, in some contexts, deep uncertainty can be understood as the broadness of the spread of the potential consequences of climate change and the unknowability of tipping points, in other contexts deep uncertainty is understood to be the uncertainty we were not aware of having hid in the assumptions of our analysis. We address both interpretations of deep uncertainty in the recommendations described here.

Table 15: Quant.11: Uncertainty Quantification and Deep Uncertainty

ID	Recommendation
Quant. 11.1	**Embrace deep uncertainty with Storylines** **Recommendation:** Use storylines to explore deep uncertainty in a traceable and physically plausible, event-oriented manner that is aligned with how people perceive risk. **Rationale:** • Storylines offer an alternative approach to the probabilistic representation of uncertainty. They are descriptive narratives of plausible future climates (and climate extremes) that are physically self-consistent. Their emphasis is on qualitative understanding rather than quantitative precision. • Storylines improve risk awareness by framing risk in an event-oriented rather

	than a probabilistic manner, which corresponds more directly to how people perceive and respond to risk. ● Storylines strengthen decision-making through a focus on a particular vulnerability or decision point, and by including both physical and human aspects of climate change. They are naturally suited to non-probabilistic decision-making frameworks, which seek adaptation options that are robust within a context of deep uncertainty. ● Storylines provide a physical basis for partitioning uncertainty e.g. ○ the probabilistic representation of the global-scale thermodynamic response to climate forcing ○ the deep uncertainty of the dynamic regional-scale mid-latitude storm track response to climate change. ● Storyline examples: ○ The spread in the projected change of precipitation in the Netherlands is substantial with some models projecting an increase and others a decrease for the same climate forcing scenario. Storylines were used by KNMI'23 to explore increased and decreased precipitation possibilities for future climate impacts. ○ The Swiss Federal Office for Civil Protection uses storylines to prepare for a broad range of perils. For each peril, they define three storylines with increasing severity and impacts. ○ The insurance and reinsurance industries use storylines for stress-testing exposure to various weather and climate conditions. Models compute possible losses from a relevant historical event or a modified version of the historical event for a given portfolio. **Sources:** [34, 35, 73, 74]
Quant. 11.2	**Be transparent about information used to inform process-based decomposition (Storylines)** **Recommendation:** Each source of information used to prepare storylines should be presented in a transparent and auditable format. **Rationale:** ● The information used to build storylines should be open to challenge and revision as scientific understanding about the processes that inform the storylines grows. ● Therefore each source of information should be presented in a transparent and auditable format because new insights or events may trigger the need to change a climate defence strategy. ● Consecutive storylines offer the ability to monitor and digest new evidence but only if the analysis itself is transparent. **Sources:** [35]
Quant. 11.3	**Explore the sensitivity of an analysis to its assumptions** **Recommendation:** Assumptions that have been made about the sources and nature of uncertainties should be recorded and communicated. **Rationale:** ● Good practice requires that assumptions that have been made during the analysis about the sources and nature of uncertainties are recorded and

	communicated to the users. • For robust decision making, it will be important to examine the sensitivity of the decisions to alternative assumptions that could have been made, to communicate the meaning of the associated uncertainty estimates, and to provide an audit trail of the analysis. • Prioritise the communication of those assumptions that the analysis is most sensitive to. **Sources:** [65]
Quant. 11.4	**Use infographics to convey climate insights under conditions of deep uncertainty** **Recommendation:** Insights about the climate under conditions of deep uncertainty are best conveyed with infographics. **Rationale:** The quantification of uncertainty is not possible or necessarily desirable under conditions of deep uncertainty. The visualisation of uncertainty assumes that: • Uncertainty is both knowable and identifiable. • Uncertainty is quantifiable. • The quantification of uncertainty is beneficial, applicable to the decision task, and usable by the decision-maker. • Deep uncertainty is perhaps best conveyed using infographics. Be conscious that uncertainty visualisations often reflect what researchers think decision-makers need to know rather than what they have asked to know. **Sources:** [29, 30, 55, 63]
Quant. 11.5	**Use Games to enhance engagement with deep uncertainty** **Recommendation:** Use games to support learning and provide analogous frameworks for real-world dialogue about the impacts of an uncertain climate. **Rationale:** • Games are a fun but serious way of helping humanity tackle the complexities, volatilities and uncertainties that could be hallmarks of the "new normal" for the global climate. • For example the "Decisions for the Decade" game that was developed by the Red Cross Red Crescent in collaboration with the World Bank. It explores both risk and deep uncertainty, and elicits an intuition about how climate change increases uncertainty. • Games can be an effective way to support learning and to provide an analogous framework for real-world dialogue about key aspects that influence long-term investment choices in an uncertain climate. **Sources:** [36]

Insights and recommendations from interviews

This section presents the insights from a set of interviews with providers from both the public and private sector. Particularly, we would like to acknowledge the participation of representatives from KNMI, NebboWeather, Lobelia, MeteoClim del Grupo WDNA, Geoskop, and Eoliann. Their insights were gathered in separate one-to-one interviews, synthesised, compared, and mixed, so that they could be presented here anonymously.

Disclaimer — The opinions presented here do not necessarily reflect the views of all companies and public institutions in the sector, may evolve over time, and should not be interpreted as the position of the authors of this document. In addition, given the limited scope of this work, the results should not be considered statistically representative of the market as a whole.

Nevertheless, we believe that this effort contributes to bridging the persistent gap between the private and public sectors, which rarely exchange views despite the clear need to do so in order to build an ecosystem that benefits all.

To improve the readability of this section, we have divided the insights into three categories:

1. The Art of Communication
2. Client Dynamics and Expectations
3. Trust, Transparency, and Standards

Table 16: Interview Insights and Recommendations

ID	Insights and Recommendations
The Art of Communication	
1	**Speak the Customer's Language** **Insight:** Technical climate terminology often falls flat outside specialist circles. **Recommendation**: Successful providers adapt their vocabulary to the specific jargon and communication styles of the sector they are addressing, ensuring the message resonates with the client's internal culture.
2	**Ditch the Report for the Reel** **Insight:** Lengthy emails and dense PDF reports are losing ground to modern communication formats. **Recommendation**: Today's culture favors quick, visual, and interactive content—like short videos or engaging infographics—that condense complex ideas into digestible bites.
3	**The "Traffic Light" Trap** **Insight:** While red-yellow-green systems are popular for their simplicity, they are dangerous for high-stakes decisions. Oversimplification can lead to a false sense of security. **Recommendation:** These tools should guide conversation, not serve as the sole basis for

	multi-million dollar investments.
4	**Color with Caution** **Insight:** Colors are powerful but subjective. While green usually means "good," color choices can reinforce biases or exclude those with color blindness. **Recommendation:** Be aware of the subjectivity and biases behind color meanings.
5	**Relative over Absolute Numbers** **Insight:** An absolute analysis of one scenario can leave users disoriented. **Recommendation:** Presenting scenarios through comparative or relative analysis—showing differences and trends rather than just absolute figures—helps non-experts grasp the "so what" of the data.
6	**Keep it Simple (but not Shallow)** **Insight:** There is a constant tension between making information understandable to a broad audience (even children) and maintaining scientific integrity. Finding this balance is the core challenge of climate service design.
Client Dynamics and Expectations	
7	**The "Who" Problem** **Insight:** A major hurdle is identifying who actually "owns" climate risk within a client's organization. Without a dedicated climate department, risk managers often struggle to see the value of this uncertain data or lack a process to integrate it.
8	**Vulnerability of the Newcomer** **Insight:** New clients often don't know what they don't know. This lack of expertise makes them susceptible to overly confident or "magical" marketing messages that oversimplify complex climate realities.
9	**Skill is the Real Currency** **Insight:** In practice, clients often care more about "skill" (proven performance) than "uncertainty." Many providers are put to the test through pilot projects where they must prove their models outperform the client's existing methods.
10	**The 20-Year Trust Horizon** **Insight:** Interest drops significantly for data projected beyond 20 years. Clients either view the uncertainty as too high or feel they cannot realistically make business decisions that far into the future.
11	**Co-production is a Marathon** **Insight:** Building a climate service isn't a transaction; it's a collaborative process. It requires significant time, continuous learning, and a degree of humility from providers and clients to truly tailor the service to a client's specific needs.
12	**The Dangerous and Attractive "Mean"** **Insight:** Relying solely on the ensemble mean is often an oversimplification that leads to poor decisions, but it's far easier to act upon than dealing with uncertainty. Apparently, some clients, when left to their own demise, decide to use solely the mean. Taking this

	into account, providers try to educate their clients and simplify the information into terciles or predictive intervals to keep the information actionable while preserving uncertainty information.
13	**One Size Fits None** **Insight:** There is a trade-off between operational efficiency and specificity. Global, "one-size-fits-all" methods are cost-effective but may fall short of specialized, regional approaches that attempt to account for local nuances.
14	**The Budget Bottleneck** **Insight:** Resource constraints dictate the science. Budget limits determine whether a provider uses dynamical downscaling, how many models they include in an ensemble, and the depth of the validation process.
15	**The Myth of "Truth" in Data** **Insight:** Observational datasets (reanalyses) are not absolute truth. **Recommendation**: Providers should verify these datasets against in-situ (on the ground) data, acknowledging that even our historical references have limits.
16	**Data Scarcity for Extremes** **Insight:** Modeling extreme events is hampered by short data records, which is often insufficient for extracting meaningful patterns for rare, high-impact events.
17	**The Complexity of Ensembles** **Insight:** Ensembles are often "ensembles of opportunity" rather than perfectly designed systems. Without transparency regarding model weights, overlaps, and shared components, selecting the right post-processing method remains a significant challenge.
Trust, Transparency, and Standards	
18	**Skepticism and the "Weather" Bias** **Insight:** Non-experts often distrust climate models because of short-term weather forecast errors. **Recommendation**: Overcoming this requires clear education on the difference between daily weather variability and long-term climate trends.
19	**The Humility Advantage** **Insight:** In many markets—particularly Europe—humility is increasingly seen as a mark of credibility. **Recommendation**: Acknowledging the limits of a model and being honest about what cannot be quantified builds more long-term trust than "magical" claims.
20	**Openness in Shades of Grey** **Insight:** Transparency is a spectrum. While peer-reviewed publications boost reputation, they often lag behind evolving internal methods. Furthermore, proprietary methods and industrial secrecy often limit how much a provider is willing to disclose.
21	**Rights and Obligations** **Insight:** A healthy climate service market requires shared responsibility. While clients

	have a right to clear documentation, providers are increasingly using disclaimers to ensure clients acknowledge the inherent risks and uncertainties in the data they receive.
22	**Different Strokes for Different Sectors** **Insight:** Uncertainty needs vary by industry. A bank might prioritize statistical portfolio performance, while an infrastructure planner needs to find the single weakest point in a physical system. Standardized outputs must remain flexible enough to serve these diverse priorities.

Conclusions

In the preparation of this report the authors aimed to provide the reader with the information needed to be as open as possible about uncertainty.

Openness about uncertainty is a necessary requirement if decisions are to be made that are based on a realistic appraisal of the evidence. However, the delivery of uncertainty information must not be so much that it leaves decisionmakers unable to act, likewise for the delivery of information about assumptions. The full disclosure of uncertainty and assumptions should be paced and prioritised according to their impact on the outcomes of an analysis.

A challenge remains on how to structure the delivery and reporting of uncertainty information. The recommendations in this report suggest that climate communication is clearest if it begins with what is known and follows this with information about uncertainty and other caveats. In all cases the delivery of uncertainty information must be suitable for the context and suitable for the intended users.

The report offers numerous methods to convey uncertainty information. It is recommended that communicators develop a range of strategies to convey uncertainty and that they seek feedback from their intended audiences about how the uncertainty information has been understood. A strong recommendation is that uncertainty phrases should always be supported with numerical information about uncertainty.

For transparency, uncertainty information should be made available and passed along through all steps in the climate information value chain. The nature of the uncertainty will guide what information can be reported. For short timeframes, where uncertainty can be quantified in a statistical sense, specifications exist about how information should be structured. For longer timeframes, the information pathway is more about conveying the nature of how the uncertainty space was evaluated via scenarios and climate projections and the building of ensembles. Transparency does not require the disclosure of proprietary methods.

The purpose of uncertainty information should be for users to understand both the potential value of the forecast or projection along with its limitations. The report addresses strategies for the quantification of uncertainty to do with climate extremes, sub-seasonal and seasonal forecasting, decadal prediction and climate projections.

It is not always possible or helpful to quantify uncertainty. Under conditions of deep uncertainty where the projected spread of the potential consequences of climate change are broad, uncertainty is best captured with narrative approaches such as storylines, infographics, and even games. Nevertheless, each source of information used to prepare an assessment should be presented in a transparent and auditable format because new insights or events may trigger the need to change a climate adaptation strategy.

Resources

Table 17: Resources used to inform the recommendations

ID	Full citation
1	Pascoe, C. P., Dankers, R., Muñoz, Á. G., & Xavier, D. S. (2025). Preliminary best practices in climate uncertainty quantification and communication. Zenodo. https://doi.org/10.5281/zenodo.17310974
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6	Uncertainty Communication. Issues and good practice (2007) Penny Kloprogge, Jeroen van der Sluijs and Arjan Wardekker
7	Guidance Note for Lead Authors of the IPCC Fifth Assessment Report on Consistent Treatment of Uncertainties (2010)
8	van der Bles (2019) Communicating uncertainty about facts, numbers and science.
9	Dhami and Mandel (2022) Communicating uncertainty using words and numbers.
10	How to communicate uncertainty in statistics
11	Communicating quality, uncertainty and change
12	The effects of communicating uncertainty on public trust in facts and numbers
13	Approaches to presenting uncertainty in the statistical system
14	Environmental Decisions in the Face of Uncertainty. Chapter 6: Communication of Uncertainty.
15	Fischhoff and Davis (2014) Communicating scientific uncertainty
16	European Food Safety Authority. Guidance on Communication of Uncertainty.
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20	Taylor et al. (2021) Communicating Uncertainty in Climate Information for China: Recommendations and Lessons Learned for Climate Services
21	Evidence-based principles for effective communication of climate change information and associated uncertainty (see header image) and Evidence-based recommendations for the visualisation of climate information (below) (website) MetOffice, UKRI, UK Climate Resilience Programme (last visited on 30 March 2026).
22	Mearns et al. (2025): Uncertainty in Climate Change Research An Integrated Approach A **book with 26 chapters**, most are relevant to our work. Link: https://link.springer.com/book/10.1007/978-3-031-85542-9?page=1#toc
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23	Decision Support Tools for Complex Decisions Under Uncertainty Decision Support Tools for Complex Decisions under Uncertainty was edited from contributions from many in the AU4DM* network. It sets contexts for decision-making, particularly focusing on the types of uncertainties that decision-makers may encounter, describes the decision-making process, and provides various tools for the decision-making process, and relating them to the type of uncertainty faced. https://bit.ly/decision-support-tools (*) AU4DM = Analysis Under Uncertainty for Decision Makers Network, this was mentioned by Charlotte once
24	Visualising Uncertainty: A Short Introduction. (2020) Visualising Uncertainty: A Short Introduction is based on a review of literature on communicating uncertainty, with a particular focus on visualising uncertainty. It introduces a 12-step strategy for uncertainty visualisation and describes techniques of design thinking as well as classification schemes for visualisation techniques. Also from AU4DM. https://bit.ly/visualising-uncertainty-intro
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33	Climate ADAPT: Uncertainty Guidance (link)
34	KNMI'23 Climate Scenarios for the Netherlands: Storyline Scenarios of Regional Climate Change https://doi.org/10.1029/2023EF003983
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36	Climate Games: Red Cross Red Crescent https://www.climatecentre.org/games/2522/decisions-for-seasons/
37	Varieties of approaches to constructing physical climate storylines: A review https://wires.onlinelibrary.wiley.com/doi/10.1002/wcc.869
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