Preliminary best practices in climate uncertainty quantification and communication

Deliverable 2.3

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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 realise 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 organised.

Executive Summary

This deliverable collects examples of best practices about uncertainty quantification and communication in climate services, largely drawing from existing literature and reports. Examples and best practices were also collected from the Climateurope2 community during an online workshop on communicating climate uncertainty, held in November 2023.

The document is organised in two main parts, discussing the current state-of-the-art and best practices in uncertainty quantification (Chapter 2), and uncertainty communication (Chapter 4). The deliverable also looks into emerging strategies to deal with deep uncertainties, i.e. those that cannot be quantified (Chapter 3), and it also discusses a number of recent real-world examples for assessing, quantifying and communicating uncertainty in climate information (Chapter 5).

A set of eight main lessons learnt regarding preliminary best practices in climate uncertainty assessment and communication can be summarised as follows (see Chapter 6 for more details):

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**

Keywords

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

1 Introduction

Uncertainty is inherent to climate information and accounting for and communicating uncertainty is therefore of paramount importance to the development and implementation of climate services. Within the Climateurope2 project, Task 4 of Work Package 2 is looking at methods and practices for uncertainty and risk assessment methods to enhance the trustworthiness of climate services in climate adaptation and the management of climate risks. For the identification of risk is the starting point for climate action.

The ultimate objective of Task 4 is to develop guidelines for gathering and propagating uncertainty assessment on the whole value chain including uncertainty communication and uncertainty assessment for risks, trends and extremes. This includes modelling strategies and methods of uncertainty quantification in climate predictions, projections and forecasts as well as uncertainties introduced in the processing of data (such as bias adjustment) and the impact assessment that often underpins climate risk analyses. The task will also explore optimal communication approaches to enhance the usability of uncertainty information and thus the understanding of it by both those providing and those using climate services.

The aim of this report is to collect examples of best practices in uncertainty quantification and communication in climate services as well as related fields. The report draws largely from existing literature and reports. Examples and best practices were also collected from the Climateurope2 community during an online workshop on communicating climate uncertainty that was held in November 2023. During the workshop, participants discussed how users of climate information deal with uncertainties and how providers of climate services should communicate about uncertainties in ways that enable users to extract the information they need.

The report is divided into two main parts, discussing the current state-of-the-art and best practices in uncertainty quantification (Chapter 2) and communication (Chapter 4). The report also looks into emerging strategies to deal with deep uncertainties that cannot be quantified (Chapter 3). It discusses a number of recent examples in practice for assessing, quantifying and communicating uncertainty in climate information (Chapter 5). Finally, the report will identify some emerging themes (Chapter 6).

1.1 Uncertainty: concepts and definitions

The word "uncertainty" means different things to different people, and in different contexts. In statistics and data science, for example, uncertainty is often used in relation to the dispersion of data points and may be quantified as variance or standard deviation. In a broader context, uncertainty is often used to refer to the unpredictability of future events and their potential impact on decision-making.

Based on earlier assessment reports, the Intergovernmental Panel on Climate Change (IPCC, 2021) defines the concept of **uncertainty** as:

> *"A state of incomplete knowledge that can result from a lack of information or from disagreement about what is known or even knowable. It may have many types of sources, from imprecision in the data to ambiguously defined concepts or terminology, incomplete understanding of critical processes, or uncertain projections of human behaviour."*

Uncertainty may also arise through the processing of data, for example by interpolation (e.g. a statistical or physical model-based interpolation of a field between available estimates to create a more spatio-temporally complete estimate), or when estimating trends. Uncertainty may be represented by quantitative measures (e.g. a probability density function) or by qualitative statements (e.g. reflecting the judgement of a team of experts) (IPCC, 2021).

At a fundamental level, a distinction can be made between **aleatory uncertainties** that can be treated as a random variable and may be expressed in terms of probabilities, and **epistemic or deep uncertainties** that include concepts such as ambiguity, reliability, inconsistency and surprises which are not easily represented as probabilities (Beven et al., 2018a). The IPCC 6th Assessment Report also acknowledges the concept of deep uncertainty (IPCC, 2021):

> *A situation of deep uncertainty exists when experts or stakeholders do not know or cannot agree on: (1) appropriate conceptual models that describe relationships among key driving forces in a system; (2) the probability distributions used to represent uncertainty about key variables and parameters; and/or (3) how to weigh and value desirable alternative outcomes.*

Deep uncertainty, therefore, refers to a state of incomplete knowledge and understanding that goes beyond standard (aleatory) uncertainty. It involves fundamental ambiguity about the underlying system, its dynamics, and the relevant decision-making context.

1.2 Sources of uncertainty in the climate-impact modelling chain

Uncertainty may arise in all stages of a typical climate services value chain, starting with the climate data itself. Even if the climate information is based on observations, there will be some uncertainty arising from measurement error or interpolation of point measurements to larger areas, among other sources.

When dealing with information about future climate change, it is common to discriminate three main sources of uncertainty: natural variability, scenario uncertainty and model uncertainty (see, e.g. Hawkins & Sutton 2009, 2011). The relative importance of these three sources is not static but depends on the time horizon of interest (Figure 1.1), the study region and the variable under consideration. Natural variability is especially important at shorter timescales (i.e. years to decades) as it may mask any longer-term changes and trends. Nonetheless, the interaction between natural climate variability and climate change can non-linearly impact uncertainty of extreme values across timescales (e.g. by modifying the tails of the distribution or the type of distribution itself).

At longer timescales, climate projections are uncertain first and foremost because we are uncertain about future levels of greenhouse gas emissions and concentrations, which in turn depend on the ambitions and implementation of climate policies, and on how human society will develop. Projections of long-term climate change are therefore based on a set of assumptions, or scenarios, about how these factors will evolve. The sixth assessment report of the IPCC adopted five Shared Socio-economic pathways (SSPs) that examine how global society, demographics and economics might change over the next century (Riahi et al., 2017).

Uncertainty also arises from the use of models. It is common to subdivide uncertainty within the modelling process into (1) uncertainty about the model structure or, in other words, about how to represent the physics of the system; (2) uncertainty about the input data and model parameter values, which extends to the data used for model calibration and evaluation; and (3) the residual unpredictability of events for given models and parameters.

A fourth source of uncertainty is particularly relevant in seasonal to decadal climate prediction, and relates to the initial conditions, where small errors in the initial state of the model can grow into marked differences in the development of the climate system (Suckling 2018).

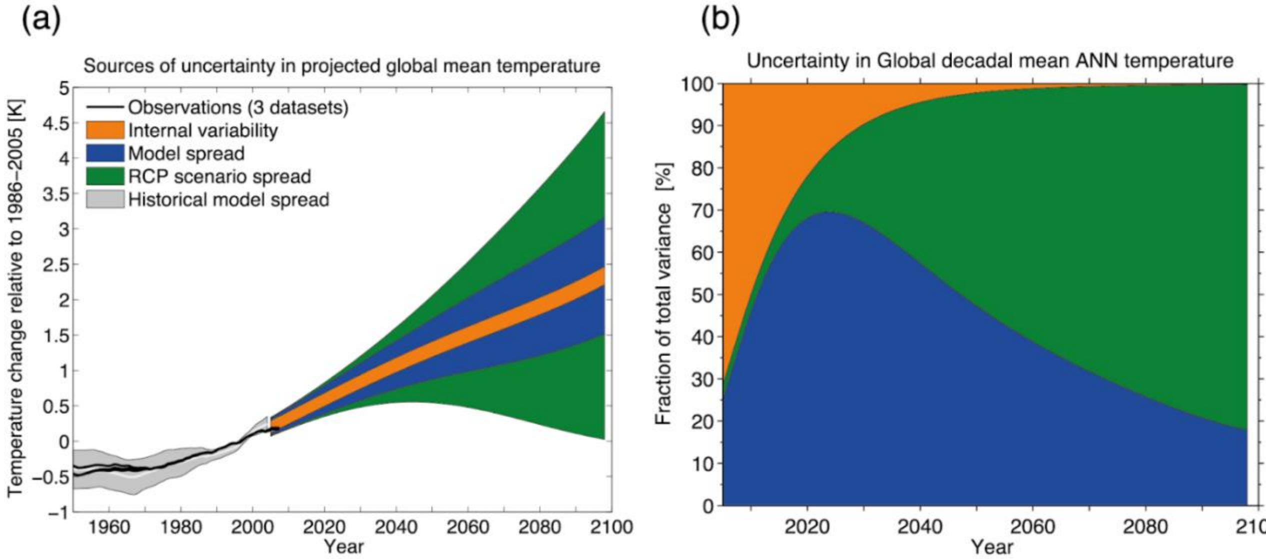

Figure 1.1: Sources of uncertainty in climate projections as a function of time horizon based on analysis of CMIP5 results, presented as a plume (a) and as a fraction of the total variance (b). (a) Projections of global mean decadal mean surface air temperature to 2100 together with a quantification of the uncertainty arising from internal variability (orange), model spread (blue) and RCP scenario spread (green). (b) Fraction of variance explained by each source of uncertainty. Note Figure (b) could be misinterpreted as showing that model spread is decreasing after the 2030s, while in fact it keeps growing throughout the century. From Chapter 11 of the IPCC WGI AR5 and Hawkins and Sutton (2009, 2011).

However, uncertainties not only arise in the production of climate data and information. It is important to consider the entire value chain, which includes data processing steps such as bias correction and downscaling; impact modelling and assessment; risk evaluation; and adaptation responses (Wilby & Dessai (2010). Each component in this "cascade" will have its own associated uncertainties (Beven et al. 2018a; see also Kundzewicz et al., (2018) and Dankers & Kundzewicz (2020) for a more comprehensive discussion). Even the communication of information may add uncertainty as a recipient may not understand or interpret the climate information as intended by the producer.

Walker et al. (2010) describe a categorisation system for uncertainty which discriminates among three dimensions: **location, level** and **nature** of uncertainty (Figure 1.2). The location of the uncertainty, in this context, describes its position in the modelling pipeline (the layers of the cascade of Wilby and Dessai, 2010). The nature of the uncertainty describes whether the uncertainty primarily stems from knowledge imperfection (epistemic) or is a direct consequence of inherent variability (aleatory). The level (or degree) of uncertainty is about where uncertainty manifests itself on the gradual spectrum from determinism, through probability and possibility to ignorance (Dessai and Hulme 2003). Van Bree and Van der Sluijs (2014) expand the three-dimension model further to also include qualification of knowledge base and value-ladenness of choices. The first (qualification of knowledge base) relates to the evidence and reliability of the information used, the latter (value-ladenness of choices) to the extent to which choices made in the assessment are subjective.

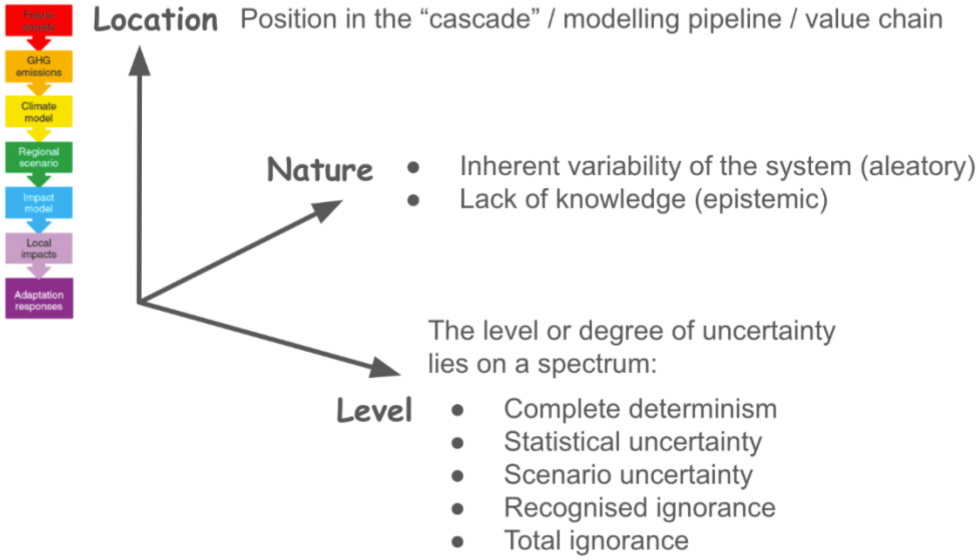

Figure 1.2: Three dimensions to categorise uncertainty: location, nature, and level (degree). Modified after Walker et al. (2010), Wilby and Dessai (2010).

2 Current practices in uncertainty quantification

To ensure transparency and maintain trust in a climate service, it is essential that uncertainties are evaluated, documented and - to the extent possible - quantified, even if they cannot be reduced. Various approaches have been developed over the years to evaluate the uncertainty in the different parts of a typical climate-impact modelling chain, many of which can also be applied in climate services. Van Bree & Van der Sluijs (2014) list a number of methods and approaches that have been used in climate change and adaptation decision making, including (in no particular order):

- Scenario analysis
- Expert elicitation
- Sensitivity analysis
- Monte Carlo simulations
- Multi-model ensemble analysis
- Bayesian methods
- Numerical Unit Spread Assessment Pedigree
- Fuzzy sets / imprecise probabilities
- Stakeholder analysis
- Quality assurance / quality checklists
- Extended peer review / review by stakeholders
- Wild cards / surprise scenarios

2.1 Uncertainty quantification in climate modelling

2.1.1 Multi-model ensemble

The standard way to evaluate climate model structural uncertainty has been through model intercomparisons, notably in the various phases of the Coupled Model Intercomparison Project (CMIP) that have been organised since 1995. By running experiments in a standardised way, model intercomparison projects (MIPs) allow the creation of a multi-model ensemble that can be used to explore the effect of structural uncertainty in the model formulation on the simulation of a key variable, such as global mean temperature. Assuming the sample of models is large enough, the performance of the ensemble as a whole can be summarised using statistics such as the ensemble mean, which in many cases has been found to outperform any individual model when comparing with observations.

However, care must be taken when analysing the results of multi-model ensembles, as the usual statistical assumptions may not hold. Many multi-model ensembles are in fact “ensembles of opportunity” and were not designed for such a statistical analysis at the outset. A key concern is to what extent these models can be considered independent. For the Coupled Model Intercomparison Project CMIP5 ensemble of General Circulation Models (GCMs), Knutti et al. (2013) established that many GCMs were not only strongly tied to their predecessors, but also exchanged ideas and code with other models, implying that the CMIP5 models were neither independent of each other nor independent of the earlier generation.

As there are likely some overlaps in the results from the individual models, and because working with the full ensemble is often not practical - the latest CMIP6 contains results from over 100 models - various techniques have been proposed in the literature to either select a representative sample of

GCMs or to weight the results from different models differently. Model selection or weighting can be done according to a number of criteria, including:

- Realism in simulating the historical climate (i.e., model performance);
- Representativeness of the spread in future projections;
- Independence of models.

The 'optimal' set of models will be different for different regions and dependent on the variable or variables of interest (see e.g. McSweeney & Jones, 2016). More recently, approaches based on information theory (Pechlivanidis et al., 2018) and expert elicitation (Sebok et al., 2022) have also been proposed.

2.1.2 Perturbed-parameter ensemble

A second type of ensemble has been applied to study the effect of uncertainty in model parameters on climate impact projections. In "perturbed-parameter" ensembles (Murphy et al. 2007; Frame et al. 2009), a single GCM is run multiple times with different values for some of the key parameters. Due to computational limits, a formal sampling of the full parameter space is out of reach for state-of-the-art, complex earth system models. In practice, the key parameters and parameter values are chosen from ranges considered plausible on the basis of expert judgement. Statistical methods have also been used to estimate the set of projections that would be produced if more comprehensive sampling of parameter uncertainty in the model could be performed (see, e.g. Sexton et al. 2012). More recently methods have been proposed to pre-filter the parameter space by finding plausible candidates from a large set of cheaper, coarse-resolution atmosphere-only simulations, at the same time ensuring sufficient diversity with respect to some predefined climate change metrics (Sexton et al., 2021). The experimental setup of perturbed-parameter ensembles allows for a more formal statistical analysis of the results; however the results are usually limited to a single model only. In other words, model structural uncertainty is not accounted for. A common finding from these studies, though, is that the uncertainty range in perturbed-parameter ensembles overlaps with those of multi-model ensembles.

2.1.3 Initial condition ensemble

A third type of ensemble samples the uncertainty in the initial conditions at the start of a model run, as small errors in the initial state can grow into marked differences in the development of the climate system. Apart from numerical weather prediction, this type of ensemble modelling is used primarily at seasonal to decadal timescales, where uncertainty due to natural variability in the climate system dominates. However, initial conditions ensembles have also been used at longer timescales to explore internal variability in the model and to better evaluate changes in the likelihood of very extreme events (e.g. Maher et al., 2019). Taken at "face value", the probability of an event may be estimated as the relative frequency of its occurrence among the ensemble members (Katz & Ehrendorfer, 2006). In practice, though, it is important to account for biases as initial condition ensembles do not sample all of the model parameters or structural uncertainty. For this reason, seasonal forecasts are increasingly based on a multi-model evaluation as well. Moreover, it is essential to use information about the past performance of a forecasting system, typically available in the form of hindcasts to try to correct for model drift, biases and spread deficiencies and, ideally, to transform raw ensemble results into estimates that are descriptive of the true probabilities of an event (Parker, 2010). The large number of simulations that are available from hindcasts has also been used to more robustly estimate the likelihood of very extreme (and therefore rare) events (e.g. Ehmele et al., 2020; Kelder et al., 2020).

2.2 Uncertainty quantification in climate data processing

The various processing steps typically applied to climate model data, including downscaling and bias correction, also have the potential to add uncertainty to the results. Although the limitations of the assumptions underpinning most bias correction techniques (and, by extension, statistical downscaling methods) have long been recognised (e.g. Ehret et al., 2012; Maraun et al., 2017), the effect of these on the outcomes of an analysis are often not assessed. The impact of the choice of different bias correction methods has been investigated in a number of studies, particularly in hydrological applications (e.g. Chen et al., 2011, 2013; Senatore et al., 2022), although it is still not common practice. Often the contribution of the bias correction method to the overall uncertainty in the results is found to be relatively smaller than the climate model or the scenario uncertainty, but in some cases the bias correction even changed the direction of the climate signal that was present in the original climate simulations (e.g. Huang et al., 2014).

2.3 Uncertainty quantification in climate impact assessment

Similar to climate modelling, the uncertainty associated with the use of climate impact models can be evaluated through model intercomparisons, as is done in, e.g. the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP, https://www.isimip.org/). Comparatively fewer studies have looked at the effect of impact model parameter uncertainty, although techniques for quantifying both structural and parameter uncertainty, such as the Generalized Likelihood Uncertainty Estimation (GLUE) method (Beven & Binley, 1992) have been around for several decades. Most of these techniques rely on Monte Carlo simulations or similar approaches with the simulation results expressed as probability distributions of possible outcomes, as opposed to a single deterministic prediction.

Fewer studies still have made a thorough end-to-end assessment of the uncertainties involved in the entire climate-impact modelling chain looking at all contributing factors,, as was done for the entire flood risk chain by Metin et al. (2018) or for hydrological impacts of climate change in Nepal by Aryal et al. (2019).

While most studies adopt a "top-down" approach exploring the accumulation of uncertainty from emission scenarios to global climate response to regional or local impacts, some have also proposed a "bottom-up" approach starting from the impacted system and exploring how resilient it is to changes and variations in one or more climate variables (Van Bree & Van der Sluijs, 2014). Such a bottom-up approach is focused more on resilience of the system and how adaptation can make it less prone to uncertain and largely unpredictable changes in climate.

An example of a more bottom-up approach is the use of impact-response surfaces where an impact model is used to evaluate the response of a system across a range of conditions. Not only does this allow for a more rigorous testing of the impact models (across many possible future conditions), but it also makes it possible to identify critical impact thresholds which might be missed if only a few climate scenarios are evaluated (Fronzek et al., 2022). Examples of this approach include the scenario-neutral approach proposed by Prudhomme et al. (2010) for fluvial flood impacts in the UK; and the application of response surface diagrams for evaluating climate change impacts on crop production by Van Minnen et al. (2000). Pirttioja et al. (2019) used a similar approach to evaluate adaptation options to crop yield shortfalls under climate change.

2.4 Passing uncertainty information on down the value chain

Especially when using a top-down approach, the different processing steps in a typical climate-impact modelling chain can give rise to what has been called a "cascade of uncertainty" (Wilby & Dessai, 2010; Figure 2.1).

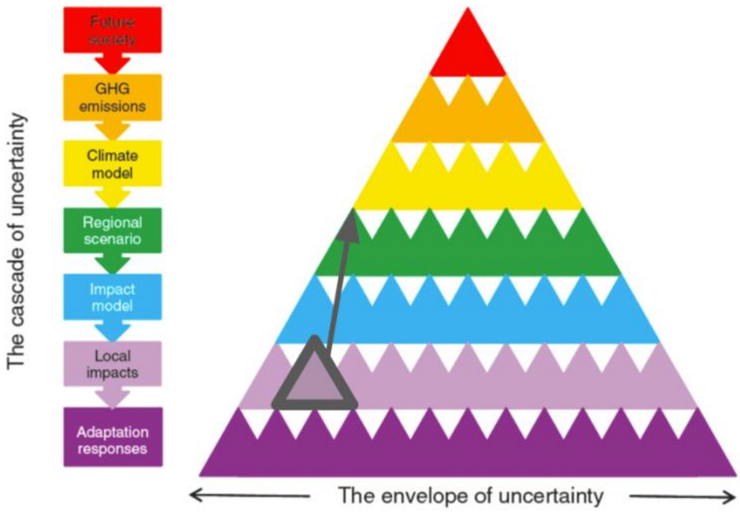

Figure 2.1: The cascade of uncertainty illustrating the potential growth of the envelope of uncertainty and the scale of the uncertainty provenance task. In practice, a bottom-up approach that begins with climate impacts will reduce the communication challenge to a set of discrete pathways. Modified after Wilby and Dessai (2010).

Uncertainty information is generated upstream and passed on downstream. Each step of the cascade (or value chain) will have uncertainty associated with it that needs to be passed on and **understood** by all subsequent users of the data or information.

While a climate service may need to keep a provenance record of the full depth and breadth of the cascade of uncertainty for its data holdings (Figure 2.1), the specific uncertainty information to be communicated for any one study will only be that which is representative of the actual data used, and tailored to the intended audience, careful documentation of the assumptions of a study notwithstanding.

Each step in the cascade or 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. SSSOM is analogous to the I-ADOPT interoperability framework for observable properties developed by the Research Data Alliance (RDA) working group for InteroperAble Descriptions of Observable Property Terminology (Magagna et al., 2021) described in Climateurope2 Deliverable 2.1. However, SSSOM is also able to explicitly capture the imprecision, inaccuracy and incompleteness of mapped concepts.

2.4.1 Uncertainty in decision making frameworks

One of the reasons why uncertainty information needs to be passed along the value chain is that it has the potential to make a difference to the decision that is being targeted by the climate service. At the same time, an uncertainty assessment has to be appropriate to the type of the decision being made, because of the time and effort being involved (Beven et al., 2018b) and the demands of clear communication.

If the level of uncertainty can be described probabilistically, a classic risk approach (e.g. a cost-loss decision model) may be used. However, in a climate change context, this is rarely the case. The main drivers of climate change (which include economic development and population growth) are inherently uncertain, especially at the longer term, and can only be explored using a scenario approach. Moreover, at a detailed level our understanding of the Earth system is rather 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. Van Bree & Van der Sluijs (2014) describe three steps to account for uncertainties in a decision framework:

1. Identify and characterise sources of uncertainty;
2. Assess (weigh, appraise, and prioritise) sources of uncertainty;
3. Select and apply methods for dealing with uncertainties.

The first step is likely to result in a long list of uncertainty sources and could be approached by analysing each step of the value chain or assessment process, or by considering where in the assessment the different types of uncertainty may occur.

In the second step, the relative importance of each uncertainty source can be evaluated by its impact on the final decision or outcome. This may be done by performing a sensitivity analysis or, if quantification is not possible, could be based on expert judgement.

In the third step, some of the key uncertainties and their impact on the final decision may be analysed and characterised in more detail. Van Bree & Van der Sluijs (2014) highlight that the uncertainties will need to be re-evaluated throughout the assessment process, as it may not be possible to identify, prioritise and characterise all sources of uncertainty right at the start.

To be useful in a decision-making process, the uncertainties obviously need not only to be analysed and described, but also communicated to the decision- or policy-maker. It is therefore important to evaluate which uncertainties are most relevant for the decision at hand, and - if relevant - identify options that are robust given these uncertainties (Van Bree & Van der Sluijs, 2014). The way that information is presented can also have an impact on its interpretation and the decisions that are made on the basis of it. To avoid misinterpretation, decision makers should be provided with a fuller understanding of the context of the information that is given to them, yet not so much information that it would overload them. For instance, 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 situation.

Some practical examples of how uncertainty information is used to inform climate adaptation decisions can be found in Lourenço et al. (2014).

2.4.2 Example of passing uncertainty information on through the value chain

An example of how quantitative uncertainty information can be used in decision-making is provided in this section.

Technical products provided today by National Meteorological Services and related institutes mainly involve forecasts of precipitation and mean, maximum and minimum temperature. These products lead in general to different managerial actions for different sectors, and therefore stakeholders normally need to go one step further in order to use them for their specific interests, for a hazard only becomes a risk if there is a vulnerability to it.

Therefore, a hazard-oriented approach alone is not enough because of its lack of information on the local sensitivity, exposure and adaptive capacity of the population. An adequate, comprehensive approach requires risk assessment, involving the difficult problem of satisfactorily quantifying both hazards and vulnerabilities for the specific sector (e.g. water availability, agriculture, health or energy managements), region of the world, and time scale (e.g. short-term, intraseasonal, seasonal, decadal, long-term) of interest (e.g. Muñoz et al. 2012). Unfortunately, due to the complicated character of the addressed problem, there is no unique methodology to quantify the risk, and different approaches are employed for different activities.

These issues make it extremely difficult to compare risk indices on different regions of the world, or even among different sectors (e.g. agriculture and health) for the same geographical region. Moreover, in the cases where risk estimations are available, they tend to exclude information on the associated uncertainties.

A way to circumvent these problems is to use a probabilistic risk management approach (e.g. Mora and Keipi, 2006; Mora, 2009; Muñoz et al., 2012), which permits to operationally define a probabilistic vulnerability distribution that is by construction consistent with both the hazard and risk probability density functions. At its core, this approach directly identifies risk with key indicators for decision makers, such as damage or cost, for which real data exists, and from which an empirical (or fitted) probability distribution can be obtained.

To illustrate the case with a real-world example, consider the annual, total maïze yield production (in hectograms by hectare, Hg/Ha) for Guatemala, from 1961 to 2005 (Figure 2.2). The maïze yield can be translated into damage cost, for example in hundred of thousands US$, and a probability density function describing the probability distribution can be directly defined from the data record. For the sake of simplicity, assume that such a distribution follows a Gaussian distribution (as in the Figure 2.2) –nonetheless the distribution does not need to be a Gaussian one. In that case, a natural measure of uncertainty is provided by the dispersion parameter of the distribution, or the standard deviation in this case.

A similar approach can be followed for the hazard, which in the example of Figure 2.2 is measured via the Palmer Drought Standardised Index (PDSI), which also conveys information on the related uncertainties via the corresponding probability distribution (see example in Figure 2.2).

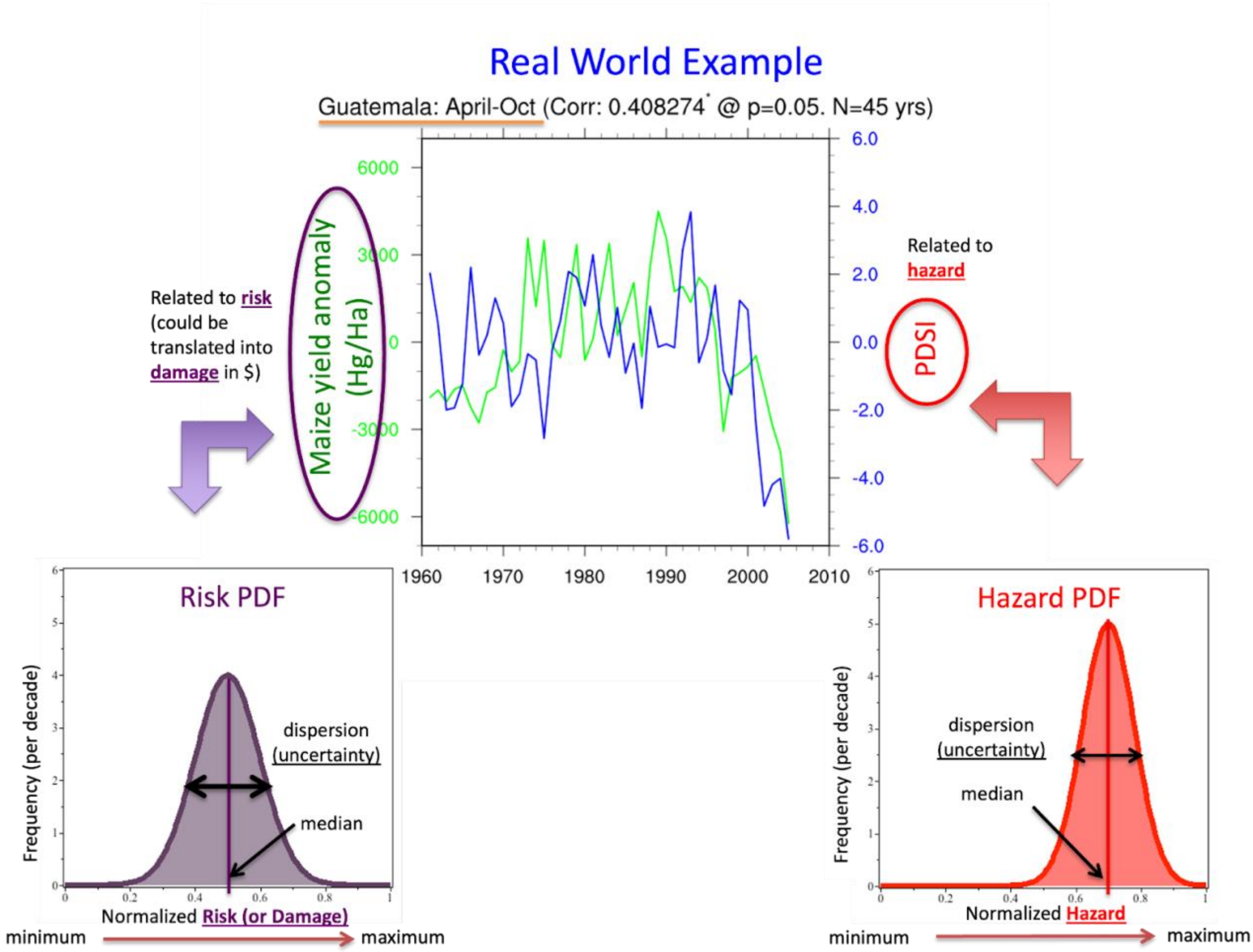

Figure 2.2: Illustration on how to define the risk and hazard probability density functions and related definitions of risk, using real maïze yield data for Guatemala (green time series curve). In this example, the key hazard is related to droughts, as measured by the Palmer Drought Standardised Index (PDSI, blue time series curve).

As suggested by Muñoz et al (2012), it is obvious that, given that the probability density functions for the risk and the hazard are known, a risk manager can mathematically define the associated vulnerability's probability density function that is consistent with both the risk and the hazard ones.

Furthermore, it is possible to then define which vulnerability distribution is required to obtain a risk distribution that the decision makers can cope with, i.e. a re-engineering of the vulnerability distribution given the knowledge of the present and future hazard distribution, and considering the desired or manageable risk distribution (Muñoz et al., 2012). For example, the risk manager might want to have a distribution that provides the most part of the probability distribution that corresponds to low values of risk. A possible choice for such a probability distribution is the exponential distribution (on the left panel of Figure 2.3).

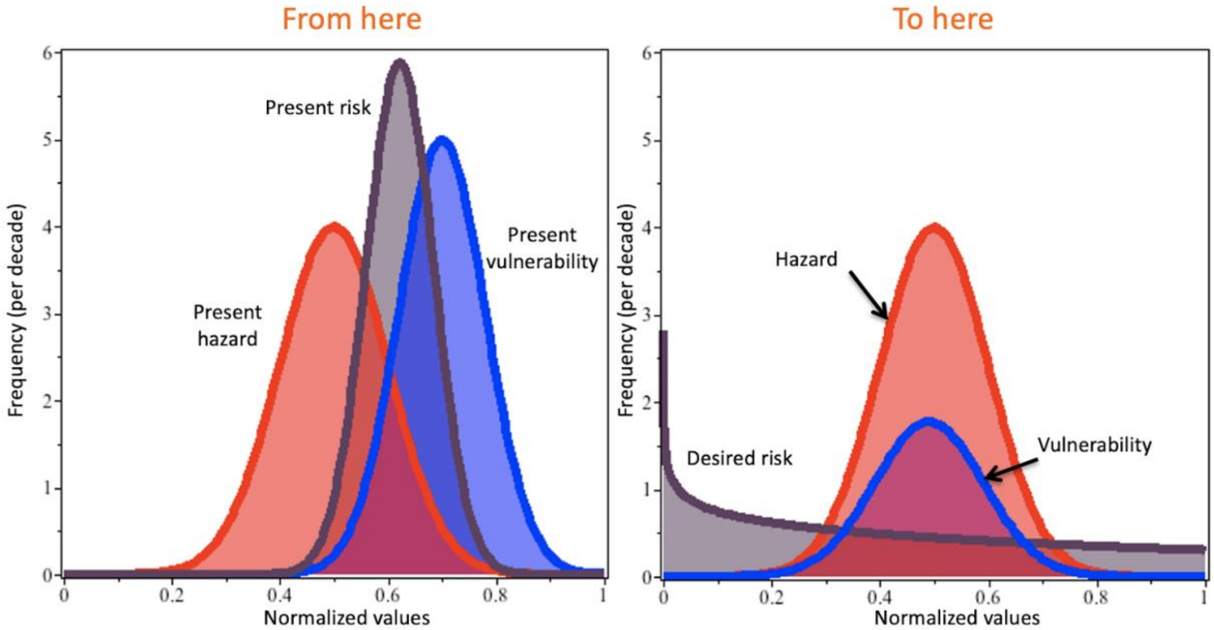

Figure 2.3: Conceptual example illustrating the re-engineering of vulnerabilities and management of the related uncertainties.

Overall, the approach enables decision makers not only to quantitatively assess risk and the related uncertainties, but also to support the choice of strategies and tasks that will help achieve a certain desired vulnerability distribution (that translates into concrete exposure, sensitivity and adaptive capacities for the population).

3 Strategies for deep uncertainties

3.1 Understanding deep uncertainty

When a system is well understood and there are good measurements available, then uncertainty can be presented using statistical methods and probabilities as is commonly the case for weather forecasts. Uncertainties associated with limited knowledge, for example about future socio-economic and technological developments and about certain aspects of the climate system, are more appropriately conveyed with the use of scenarios that indicate “what if” situations.

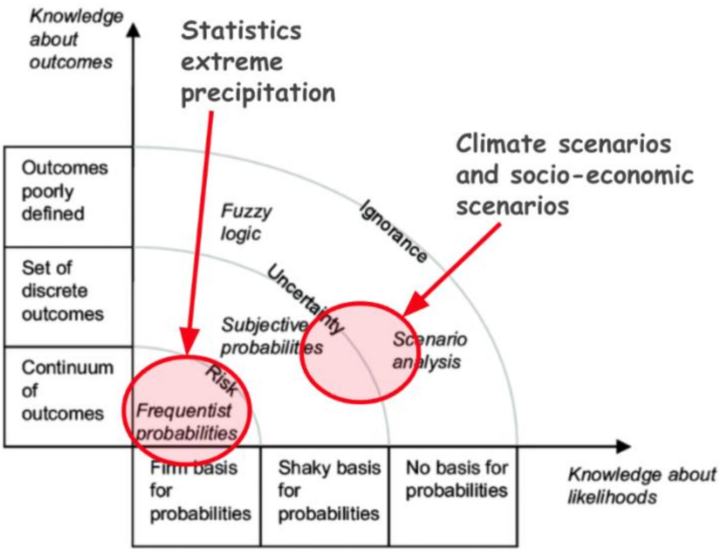

Figure 3.1: Continuum of uncertainty. The realm of probabilities and other methods to represent uncertainty when comparing the knowledge about outcomes with the knowledge about likelihoods. Modified after Dessai and Hulme (2003), Stirling (1998).

Epistemic or deep uncertainty refers to a state of incomplete knowledge and understanding that goes beyond standard uncertainty. It involves fundamental ambiguity about the underlying system, its dynamics, and the relevant decision-making context. This concept is related to the notion of “vague uncertainties” of Budescu and Wallsten (1987) and similar concepts dating back to at least the 1920s. Deep uncertainty is often characterised by the inability to assign precise probabilities to future events or to fully comprehend the system's complexity. It often involves unknown unknowns, where potential future scenarios and their likelihoods are difficult to define.

Deep uncertainty challenges traditional decision-making frameworks that assume a known and probabilistic future, requiring approaches that can navigate ambiguity, embrace scenario thinking, and incorporate adaptive strategies to account for the inherent unpredictability of certain situations. It also has implications for communication as overly precise numerical expressions of the likelihood of a particular event or outcome are potentially misleading.

3.2 Accounting for deep uncertainty

A common approach to navigating and dealing with deep uncertainty is employing scenarios. Scenarios involve the creation of plausible and divergent narratives or storylines that outline different potential futures. By exploring a range of scenarios, decision-makers can better understand the spectrum of possible outcomes and prepare adaptive strategies that are robust across various eventualities.

There is no single way of establishing the impact of deep uncertainty on the outcomes of a risk analysis in a more quantitative sense, although methods have been proposed that allow combining probability distributions with measures of belief and disbelief, such as the Dempster-Shafer method or subjective logic.

Beven et al. (2018a) suggested that 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 (Beven et al., 2018b).

A formal elaboration of this idea can be found in a recommended practice for assurance of simulation models that was compiled by the accredited registrar and classification society DNV (2021). By combining information about the uncertainty associated with the model with an assessment on the consequences of a possible wrong decision that the model is supporting, the risk associated with the use of the model on the outcome can be evaluated (Figure 3.2). The categorisation of the consequences obviously depends on the context and may need to be coordinated with the user, for example for safety issues a minor could mean "one or more minor injuries" and catastrophic "multiple fatalities."

	Severity of consequence if function does not work as intended			
	Minor	Significant	Severe	Catastrophic
High uncertainty that model does not represent relevant aspects of the reality	2	3	4	Not Trusted
Medium uncertainty that model does not represent relevant aspects of the reality	1	2	3	4
Low uncertainty that model does not represent relevant aspects of the reality	0	1	2	3

Figure 3.2: Risk matrix combining a categorisation of the uncertainty associated with the use of a particular model with a categorisation of the consequences. Source: DNV (2021).

DNV also recommend using uncertainty shaping factor checklists to understand and classify uncertainty (the vertical axis in the matrix; DNV, 2021). Such checklists could be adapted for use in climate services.

Identifying and evaluating the effect of the assumptions that have been made as part of the process is therefore an important part of any risk assessment, yet it can be challenging as many assumptions are tacit and not explicit. People involved in the process may not even know that they have made assumptions, yet the assumptions have the potential to obscure a major part of the risk.

Assumptions occur at each step of the risk assessment process, from defining the scope, to selecting a workflow within that scope, to summarising the results with metrics. An awareness of where assumptions can occur and a systematic way of checking whether assumptions have been made can be very insightful.

One way to assess how critical assumptions are is through a method called assumption-deviation risk. Flage (2019) provides a framework for quantifying the criticality of a risk assessment's assumptions based on the consequences of a deviation from the assumption along three components (Table 3.1): the sensitivity of the conclusion with respect to the assumption; the strength of knowledge (SoK) supporting the assumption; and the belief in the possibility of deviations or even violations of the assumption.

An assumption with low criticality (setting I) can be considered reliable because there is little expectation that it may not be true, it has little impact on the conclusion of the assessment and the strength of knowledge that supports it is strong. Whereas risk assessment metrics based on assumptions with high criticality (settings V and VI) should be treated with caution.

Table 3.1: Quantification of the criticality of assumptions to risk assessment metrics, after Flage (2019).

		SoK label	
Belief in deviation	Sensitivity of risk metric with respect to assumption deviation	Strong	Moderate/ Weak
Low	Low	Setting I	Setting II
	Moderate/High	Setting III	Setting IV
Moderate/ High	Low		
	Moderate/High	Setting V	Setting VI

4 Best practices in communicating uncertainties

Communication of (future) climate information can be considered broadly equivalent to the communication of risk, especially if the impacts are considered as well. In its simplest form, communication can be viewed as the process of sending information or content (such as a message in natural language) in some form (e.g. as spoken language) from a sender or source to a receiver. This basic model of communication was first formulated by Shannon (1948) and has a long-standing history in risk communication and other disciplines, but it has also been criticised as it does not allow for, for example, differing purposes or interpretations.

More recently, risk communication is seen as an interactive exchange rather than a one-way transfer of information, knowledge and opinions. Höppner et al. (2010) identified five key elements of risk communication: actors, purposes, modes and channels, tools and the message itself. As a universal principle, the language and terms used have to fit the audience rather than the other way round: an expression such as ‘100-year flood’ may be interpreted differently by experts and laypeople. The content and the mode of communication has to fit the needs of the audience and the requirements of the situation. To increase the credibility of the message it is important to be transparent and acknowledge uncertainty. In other words, the content should not only be about what is known, but also about the uncertainties and what is unknown. However, in order not to overwhelm the user, the uncertainty information needs to be tailored to the audience and the mode of communication.

There are many guidelines for risk communication from diverse fields such as health, food safety, and technological and chemical risks. Some practical advice for communicating climate information more broadly is given in the The Uncertainty Handbook (Corner et al., 2015). Although some of the 12 principles in the Handbook are aimed more at dealing with climate sceptics, many of the principles could also be applied in a climate services context:

1. Manage your audience’s expectations
2. Start with what you know, not what you don’t know
3. Be clear about the scientific consensus
4. Shift from ‘uncertainty’ to ‘risk’
5. Be clear what type of uncertainty you are talking about
6. Understand what is driving people’s views about climate change
7. The most important question for climate impacts is ‘when’, not ‘if’
8. Communicate through images and stories
9. Highlight the ‘positives’ of uncertainty
10. Communicate effectively about climate impacts
11. Have a conversation, not an argument
12. Tell a human story, not a scientific one

4.1 Formats for communicating uncertainty

In text

Uncertainty can be conveyed in different ways, ranging from percentage probabilities and expressions of uncertainty to expressions of confidence and ambiguity, and indications of alternative scenarios (Morss et al., 2008; Van Bree & Van der Sluijs, 2014). Probabilistic predictions in particular can be communicated using precise numerical probabilities (for example, there is a 0.4 chance that X will occur), imprecise numerical probabilities (for example, the probability that X will occur is between 0.3 and 0.6) or probability phrases (for example, it is improbable that X will occur). (Budescu et al., 2014).

While it is preferable to communicate probability with precision, it's crucial to recognise that overly precise numerical expressions of likelihood can be misleading. People interpret and act on probability information differently, and decisions may be different when uncertainty information is vague rather than precise (Budescu and Wallsten, 1987). Spiegelhalter and Riesch (2011) suggest tailoring the expression of uncertainty to the depth of uncertainty; if doubts exist about the model's adequacy, resulting probabilities should not be overly precise, and a range may be more appropriate. Deeper uncertainties may be communicated by expressing confidence in the model based on quality of the evidence and/or a judgement about the robustness of the analysis. However, caution is needed in conveying complex or ambiguous information, as some individuals, especially those with low numeracy or optimism, may become confused or risk-averse (Spiegelhalter et al., 2011). This underscores the importance of understanding how target audiences interpret and use the information (Morss et al., 2008).

Table 4.1: Verbal descriptions of quantified uncertainty (or likelihood) in the guidance note for the IPCC Fifth Assessment Report (Mastrandrea et al., 2011). Note phrases 'More likely than not' (for probabilities above 50%), 'Extremely likely' (for probabilities above 95%) and 'Extremely unlikely' (for probabilities below 5%) have also been used. Likelihood only describes one aspect of risk, a consequence dimension is required for a more complete description.

Description	Likelihood of the Outcome
Virtually certain	99-100%
Very likely	90-100%
Likely	66-100%
About as likely as not	33-66%
Unlikely	0-33%
Very unlikely	0-10%
Exceptionally unlikely	0-1%

Since its Fifth Assessment Report, the Intergovernmental Panel on Climate Change (IPCC) has used a calibrated language of verbal descriptions of quantified uncertainty (termed likelihood) (Table 4.1) to convey imprecision in its predictions and conclusions. Here likelihood may be based on statistical or modelling analyses, elicitation of expert views, or other quantitative analyses (Mastrandrea et al., 2011). However, studies have shown that these likelihood statements are often misinterpreted by laypeople, and assumed to be closer to 50% than intended. Supplementing the verbal descriptions with numerical ranges improves the understanding and leads to a better differentiation of the terms in Table 4.1 (Budescu et al., 2014).

Visualisation

Visualisations are a powerful way to communicate information and graphics are widely used in communicating climate information. However, as with verbal descriptions, visual information may be interpreted differently by experts and laypeople. When not appropriately designed and disseminated, visualisations could be confusing or misinterpreted and lead to decisions that are not well-informed.

A key principle in visual communication is that graphs and maps need to be clear and almost self-explanatory to the intended audience. This is a challenge for the visualisation of uncertainty information, which often requires some additional explanation. Especially "deeper" epistemic uncertainties are not easily presented as visualisations. Beven et al. (2018b) point out that the visualisation itself may also introduce further uncertainties, for example as a consequence of a particular interpolation or smoothing method that has been applied, or because the user may not interpret the graphical information as intended. Visualisations that are made too precise or detailed, for example, may induce an undue belief in the model performance that is not warranted by the uncertainty in the result (Beven et al., 2018b).

While the simplest way to display uncertainty information in a map is perhaps to show two maps side by side, with one map showing the actual values and the other a measure of uncertainty (such as the standard deviation or signal-to-noise ratio). As Kaye et al. (2012) point out, this approach has the obvious disadvantage that it can be problematic to read both value and uncertainty simultaneously, as mentally overlaying maps is difficult. Kaye et al. (2012) proposed a number of guidelines for representing both magnitude and uncertainty in mapping climate data. These include:

- use a sensible sequential or diverging colour scheme;
- use appropriate colour symbolism if it is applicable;
- ensure the map is accessible to everyone, including for example colour blind people;
- use a data classification scheme that does not misrepresent the data;
- use a map projection that does not distort the data;
- attempt to be visually intuitive to understand.

Kaye et al. (2012) illustrated their approach by using a bivariate technique that adjusts the hue of a small palette of colours to show the mean or median of a variable and the saturation of the colour to indicate a measure of uncertainty in this value. However, as Daron et al. (2015) point out, there is still limited empirical evidence of how different individuals and groups interpret different visualisations of climate data, potentially leading to misinterpretations. It is important to be aware that, by translating data into information and by using different visualisation styles and techniques tailored towards a specific user community, inherently a layer of interpretation is being added (Daron et al., 2015). Collecting empirical evidence on how the audiences from diverse backgrounds interpret climate visualisations is, however, not a widely adopted practice.

Storytelling

Recently, storytelling has received an increasing amount of attention as a means to communicate climate information to a non-technical audience. Telling a story means presenting information in a narrative format, offering a way of building more sustainable and meaningful engagement because people are more used to communicating information through stories than graphs and numbers (Corner et al., 2018). Not only does the use of narratives help audiences understand complex and abstract science issues, but it also makes them easier to remember and to process relative to traditional forms of scientific communication.

Shepherd et al. (2018) argue that a storyline approach may be an effective way of communicating uncertainty in the physical aspects of climate change. They define a storyline as a physically self-consistent unfolding of past events, or of plausible future events or pathways. The emphasis of a storyline is on a qualitative understanding rather than quantitative precision. No a priori probability is assigned to a particular storyline; instead, the emphasis is placed on understanding the driving factors involved and the plausibility of high-impact events.

Shepherd et al. (2018) identify four benefits of using a storyline approach. Storylines can enhance risk awareness by framing risks in an event-oriented way, aligning with how people perceive and respond to risk. A storyline approach can also strengthen decision-making by allowing backward planning from specific vulnerabilities, incorporating climate data with other factors to address compound risks. Additionally, storylines provide a physical basis for managing uncertainty, enabling the use of credible regional models. Lastly, they help explore plausible boundaries, preventing false precision and surprises. Storylines also offer the opportunity to link the physical and human aspects of climate change. In short, when co-developed by scientists and stakeholders, event-based storylines can provide a useful way of communicating and assessing climate-related risk and feed directly into a specific decision-making context (Sillmann et al., 2021). In addition, Barclay et al. (2023) demonstrate there may also be benefits to the “storyteller” themselves, as it may help rationalising their understanding and experiencing of complex, uncertain situations.

5 Examples of uncertainty assessment and communication

The previous sections summarise what the literature has to offer on communicating uncertainties in climate information. We also wanted to gather some information about if and how these methods are used in practice. In this section we will present a number of examples of how the concept, methods and practices with regards to the evaluation and communication of uncertainty are implemented by the climate services community. With the exception of the first case study, the examples were collected from the Climateurope2 community during an online workshop on communicating climate uncertainty that was held in November 2023. In total, 83 people participated in the workshop. Three lectures were given by representatives from KNMI, DNV and the Red Cross / Red Crescent. During the workshop, participants discussed how users of climate information deal with uncertainties and how providers of climate services should communicate about uncertainties in ways that enable users to extract the information they need. Below we introduce the uncertainty communication framework used by the IPCC and summarise relevant inputs from the three workshop lectures.

5.1 IPCC AR6

The IPCC framework for characterising knowledge and uncertainties (Mach et al. 2017) is a single framework (Figure 5.1) that could be applied consistently across working groups, spanning diverse disciplines and topics. This shared framework aimed to increase the comparability of assessment conclusions across all topics related to climate change, from the physical science basis to resulting impacts, risks, and options for response.

The diagram in figure 5.1 illustrates the process IPCC AR6 authors used to evaluate and communicate the state of knowledge in their assessment. The process begins with evaluation of evidence and agreement (steps 1–3). Where possible, authors then evaluate confidence, synthesising evidence and agreement in one qualitative metric (steps 3–5). Where uncertainties can be quantified probabilistically, authors subsequently evaluate likelihood or a more precise measure of probability (steps 5–6). Note that the likelihood categories should be considered to have “fuzzy” boundaries (step 6 (CCSP, 2009)). Unless otherwise specified, assessment conclusions characterised probabilistically are underpinned by high or very high confidence. Authors present evidence/agreement, confidence, or likelihood terms with assessment conclusions, communicating their expert judgments accordingly. Example conclusions drawn from the IPCC AR6 are presented in the box at the bottom of the figure. (Mach et al. 2017)

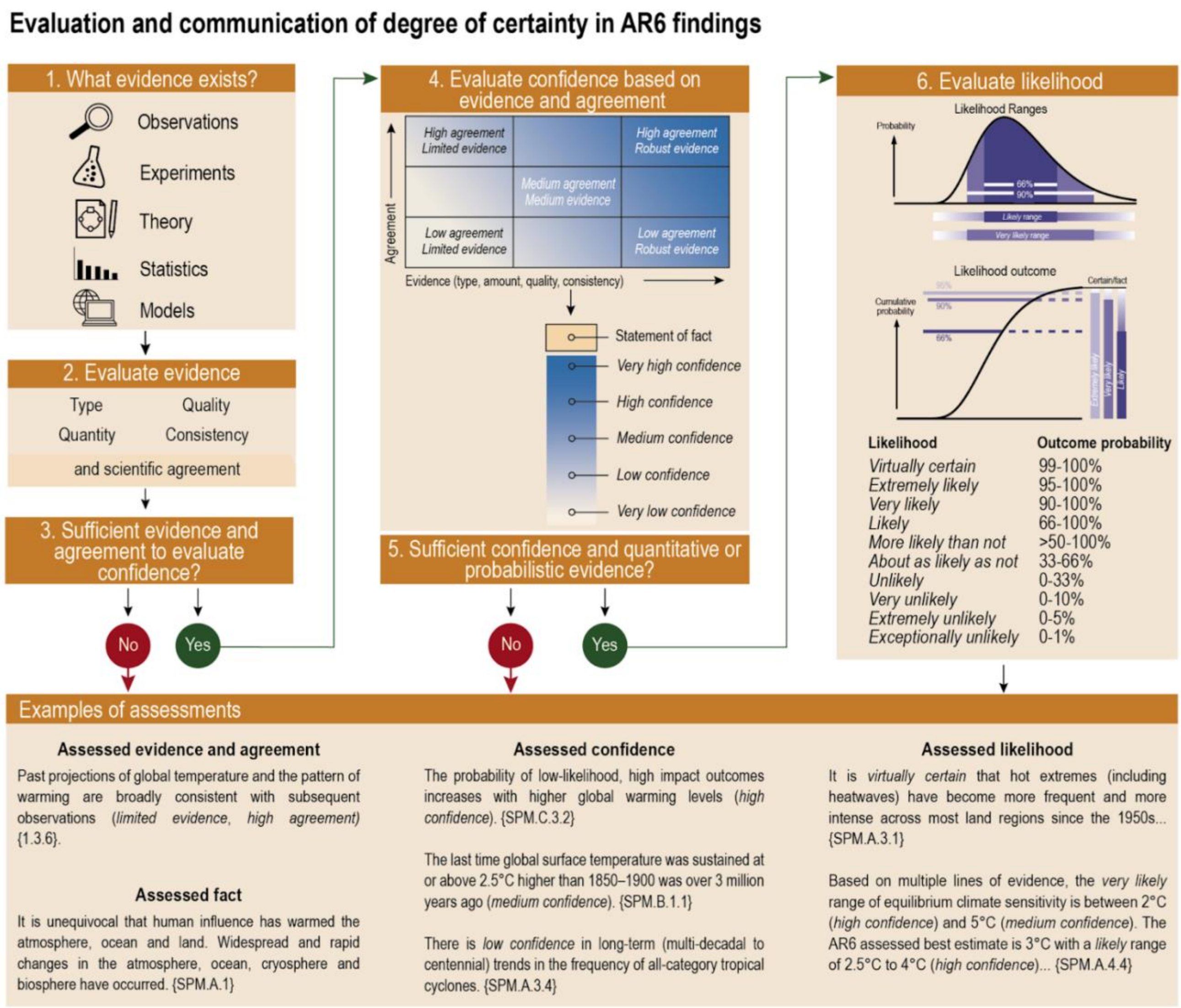

Figure 5.1: The IPCC AR6 approach for characterising understanding and uncertainty in assessment findings. The diagram illustrates the step-by-step process authors use to evaluate and communicate the state of knowledge in their assessment (Mastrandrea et al., 2010). Figure adapted from Mach et al. (2017).

5.2 National climate scenarios: KNMI'23

The Royal Netherlands Meteorological Institute (Koninklijk Nederlands Meteorologisch Instituut - KNMI) is a national knowledge institute for weather, climate and seismology. The KNMI'23 climate scenarios (KNMI, 2023) are four new scenarios which outline what the future climate in The Netherlands could look like. With the new climate scenarios, KNMI offers guidelines for policy advisers and other professionals so they can make adequate decisions to ensure a safe, liveable and prosperous Netherlands in a changing climate. Janette Bessembinder from KNMI kindly shared with us the benefit of her experience of communicating climate information and uncertainty to wider society at the Communicating Climate Uncertainty workshop held by Climateurope2[1].

[1] https://climateurope2.eu/news-events/events/events/communicating-climate-uncertainty

Establish the idea of uncertainty

The first step is to establish the idea that there is not just one prediction for the future of the climate. KNMI'23 does this by presenting information in terms of two scenarios, one associated with high CO2 emissions and another with low CO2 emissions. The simple act of presenting two possible futures conveys the concept that the future is not known (is uncertain) and, more subtly, that in the long-term, the main source of that uncertainty is uncertainty associated with how humans will collectively behave.

Present an even number of climate projections

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 the audience with 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 specific topic of interest.

Consider the most relevant climate risks

Climate communication practitioners should consider which are the most important climate risks for a specific audience. In The Netherlands there are distinct risks associated with dry years and with wet years, and sea-level rise is also a major concern. The most probable risks are often not the most relevant risks, so the simulated scenarios that inform an analysis should be those that do the best job at representing the risk situation that is of particular concern.

KNMI'23 uses a four quadrant framework of high emissions vs low emissions (representing uncertainty about future socio-economic and technological developments) and drier climate vs wetter climate (representing uncertainty about the climate system). The framework is used to convey an indication of the severity of climate risk factors for temperature change, wetter winters, extreme summer showers, drought, and sea-level rise. (figure 5.2)

This four quadrant format is able to convey whether year on year variability of a climate risk is to be expected. The severity of risk factors to do with temperature change and sea-level rise are only dependent on the emissions scenario. The severity of risk factors to do with wetter winters, extreme summer showers, and increased droughts are also dependent on whether the year is particularly wet or particularly dry.

The four-quadrant framework adopted by KNMI presents climate uncertainty in terms of a set of threats for which to be prepared. Information about threats which are specific and relevant for an audience empower climate action.

Figure 5.2: The four KNMI'23 scenarios for climate change in the Netherlands. The number of small blocks represents the extent of climate change around 2100 compared to 1991-2020. The four-quadrant framework conveys the severity of climate risk factors associated with low and high CO2 emissions and wetter or drier climate. Source: KNMI (2023).

Include the lived experience of the audience

For many people, the year-to-year variability of the climate system 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.

Including year-to-year historical variability on graphs of historical and projected climate trends gives the audience an appreciation of 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 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 (as in figure 5.3a). For box plots this could be overlaying the historical statistics with annual data points (as in figure 5.3b).

Presenting historical data using the same method as data for the projected future, with context via a representation of year-to-year variability, makes the information on the graph easier to understand.

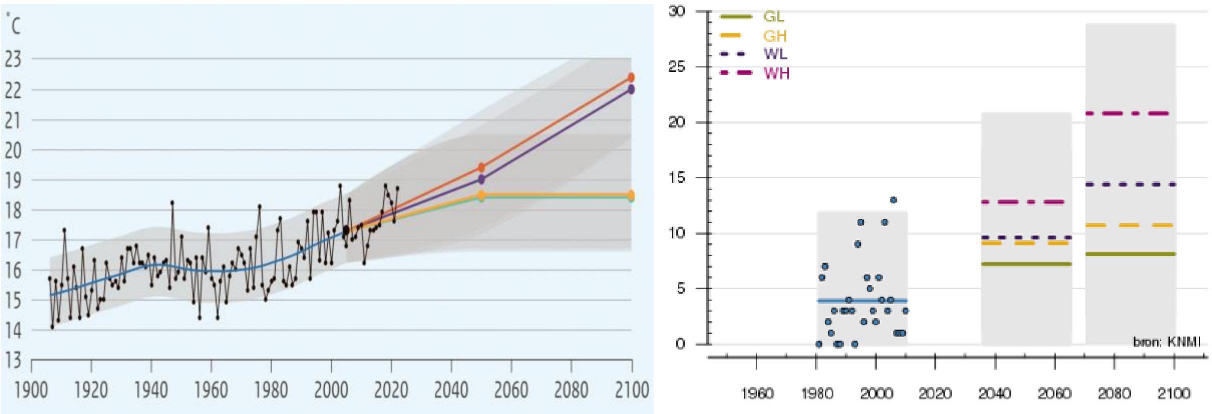

Figure 5.3: Examples of making climate graphs easier to understand by using the same method to present both historical data and data for future projections, and providing context via a representation of the year-to-year variability of the historical period. a) Time-series of historical and projected summer temperature for the Netherlands (KNMI, 2023). b) The annual number of tropical days (observed and projected) for the Netherlands.

Using maps

An effective way to convey the geographical distribution of how the behavior of a climatological index might be expected to change in the future is with a contour map. However, if the communication only provides one future instance it would convey an implicit bias towards the chosen scenario. The uncertainty of the future climate can be conveyed by showing at least two instances from different scenarios.

People like to have access to climate information that is local to them. When presenting local information, it can be better to convey the values of climate indicators in terms of their absolute values rather than as percentage changes. There is an implicit assumption that data presented as a percentage change is true for the whole of an area rather than being specific to a locality.

The language of uncertainty

Much of the language that we use as climate scientists can have a very different meaning in public life, this is particularly pertinent for the topic of uncertainty communication. It can be better to use commonly understood descriptive language in place of scientific terminology. For instance, rather than using the word "uncertainty" which implies ignorance, a better choice could be the word "range". But if the word uncertainty can not be avoided then it should be clearly explained. More examples of commonly misunderstood climate science terminology can be found in table 5.1 .

Emphasising uncertainties too much may leave people "paralyzed" and unsure of how to act. In climate change communication it is better to focus on what is known first. 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". However, we should not obscure uncertainties.

Table 5.1: Examples of climate science terminology that have the potential to be misunderstood by the public and alternative options.

Terms that have different meanings for scientists and the public		
Scientific term	**Public meaning**	**Better choice**
enhance	improve	intensify, increase
aerosol	spray can	tiny atmospheric particle
positive trend	good trend	upward trend
positive feedback	good response, praise	vicious cycle, self-reinforcing cycle
theory	hunch, speculation	scientific understanding
uncertainty	ignorance	range
error	mistake, wrong, incorrect	difference from exact true number
bias	distortion, political motive	offset from an observation
sign	indication, astrological sign	plus or minus sign
values	ethics, monetary value	numbers, quantity
manipulation	illicit tampering	scientific data processing
scheme	devious plot	systematic plan
anomaly	abnormal occurrence	change from long-term average

5.3 Risk Assessment: DNV

DNV[2] are experts in assurance (protection against events) and risk management for industry with a stated purpose to safeguard life, property and the environment. Andreas Hafver from DNV kindly gave us the benefit of his insights on risk management from an industry perspective and its relationship to uncertainty at the Communicating Climate Uncertainty workshop held by Climateurope2.

Uncertainty is a part of the risk and should not be used to take risk less seriously. In fact more uncertainty is a reason to take a risk more seriously. However, people don't like to hear about uncertainties, they want to have numbers and clear recommendations. Nevertheless, we should harness the power of uncertainty, because 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.

Understanding Risk

There are many definitions for risk, a few examples are listed below:

- Cambridge Dictionary: "the possibility of something bad happening"
- IPCC AR6: "the potential for adverse consequences"
- ISO 31000: "the effect of uncertainty on objectives"
- ISO/IEC 61508: "combination of the probability of occurrence of harm and the severity of that harm"

In general, the principle of risk is an assessment of the likelihood (degree of certainty) about a set of consequences that are either wanted or unwanted.

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[2] https://www.dnv.com/about/index.html#

A risk can be described in terms of a two axis framing of its consequences. Some consequences are wanted while others are unwanted, and some consequences are certain while others are uncertain.

The severity of the consequences of a risk will be assessed differently by different stakeholders who will have different objectives, different knowledge and different ways of knowing. The values and objectives of a society will also change through time and things that were previously not considered as risks become important to consider and vice versa.

Risk metrics and assumptions

Risk assessments often communicate risk with plots showing quantitative risk metrics (Figure 5.4). For example risk matrices of severity and likelihood, risk maps showing the geographical distribution of risk, risk radars which show how a range of scenarios score on different parameters, exceedance curves that show the frequency of events and their impact, and forecasts of some quantity of interest with some uncertainty around the predictions with maybe a critical limit to show uncertainty about when the limit will be reached.

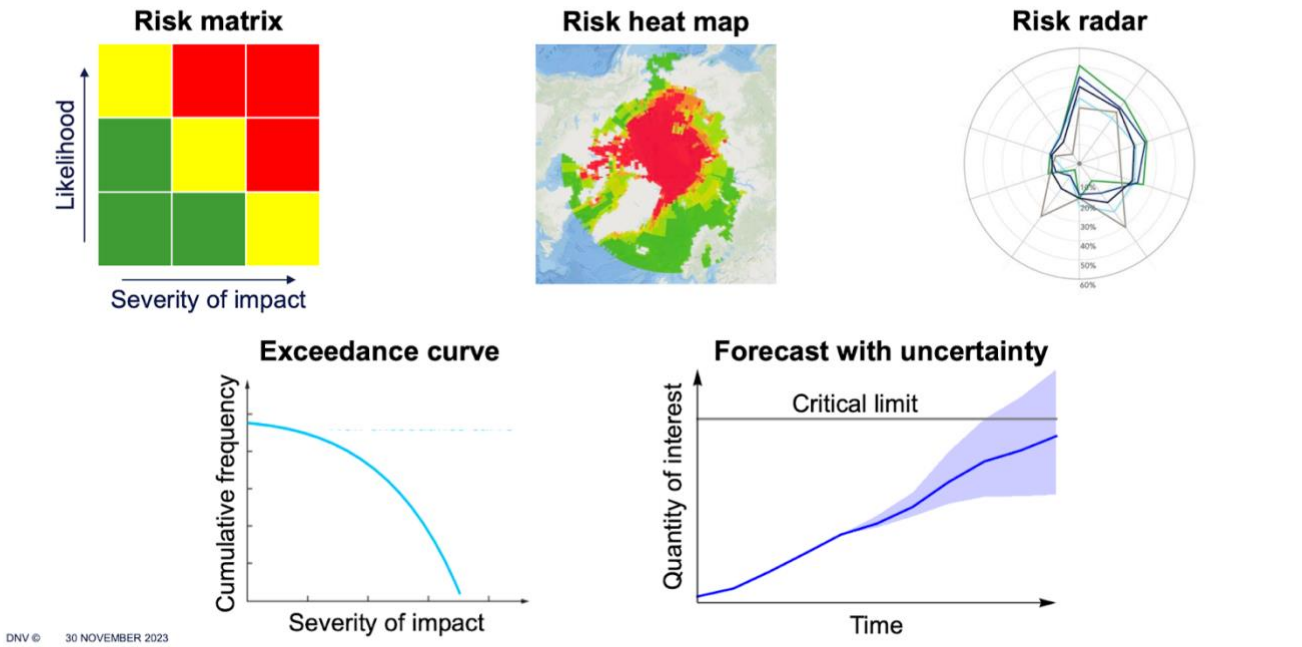

Figure 5.4: Examples of quantitative metrics for communicating risk.

However, risk is more than what we can quantify with metrics. Any risk assessment involves choices and assumptions as part of the analysis. The metrics presented to describe a risk will only capture aspects of the full risk picture. Tacit assumptions made as part of the risk assessment process have the potential to obscure a major part of the risk picture. For a more complete picture of the risk, quantitative metrics could be accompanied by an evaluation which includes: the rationale for the metric; properties of the evidence used; degree of consensus; criticality of the assumptions; and the location, nature and degree of uncertainty (see sections 1.2 and 3).

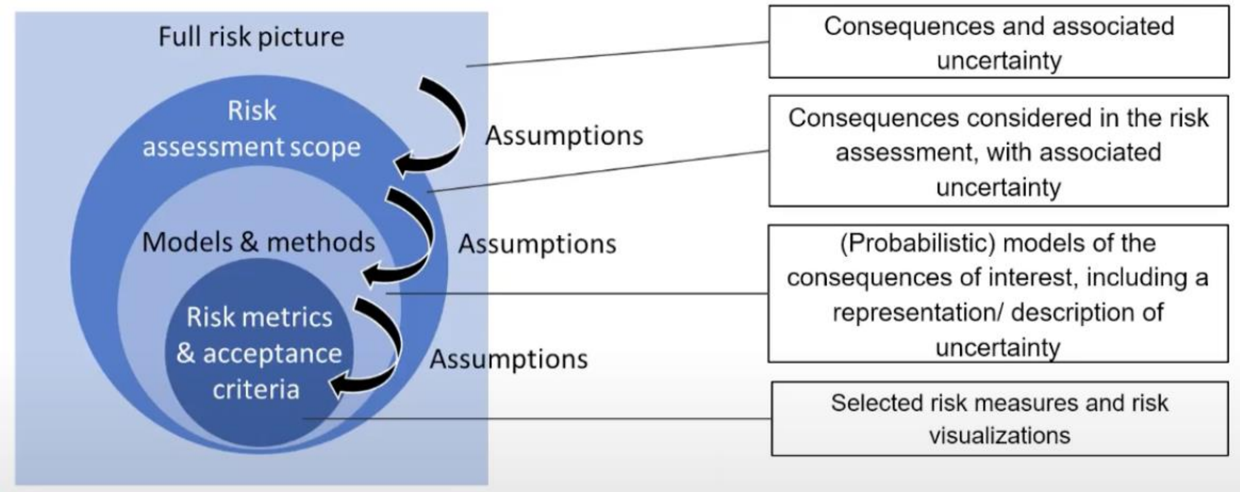

Figure 5.5: Quantitative metrics presented to summarise an assessment of risk are only part of the full picture. An evaluation of the assumptions made in the risk assessment process should also be communicated. Note that tacit assumptions have the potential to obscure a major aspect of the risk (see section 3 for more on the role of assumptions).

However, it is not always appropriate or indeed useful to communicate risk using quantitative methods (see also section 4 and 5.1). Even if a quantitative analysis is possible it may not be necessary, sometimes it is sufficient to provide a qualitative description of the risk to support a decision. On occasions where it is necessary to be more precise, the precision of the risk description should match what is supported by the knowledge.

5.4 Climate Interventions: Red Cross - Red Crescent Climate Centre

The mission of the Climate Centre is to support the Red Cross and Red Crescent Movement and its partners in reducing the impacts of climate change and extreme-weather events on vulnerable people. Christopher Jack is a climate science expert with the Climate Centre who is primarily engaged with forecast based finance and anticipatory action. Chris has become increasingly involved and passionate about integrating climate science into collaborative learning, co-production, and transdisciplinary action research processes. We are grateful to Chris for sharing his experience in this field with the Communicating Climate Uncertainty workshop held by Climateurope2.

Humanitarian Sector

Aid interventions in the humanitarian sector aim to limit the impact of rapidly emerging and evolving crises by anticipating emerging and evolving crises over weeks through months and possibly years. The humanitarian sector is characterised by high complexity with compounding and cascading risks and impact, high uncertainty with low quality or no data related to vulnerability as well as climate, and a high cost of failure. Failure to anticipate impacts can cost a lot more than acting in anticipation. The mis-allocation of funding and resources can cost lives. Within complex humanitarian contexts the relative contribution of weather and climate compared to other factors influencing a crisis is not always clear.

Development Sector

Aid interventions in the development sector aim to enable, support and encourage development in the face of climate variability and long-term change. The development sector is characterised by high complexity of climate risk governance (Who makes what decisions? Where does the money come from? There are multiple and contested agendas), and high uncertainty with lots of actors including consultants and climate service providers. From a user perspective there is uncertainty about where to get information (who to listen to and which portal to use). Therefore building trust and relationships is very important (who to trust and why to trust them).

Anticipatory Action

With anticipatory action, a warning of a crisis event allows action to be taken before the impacts occur. Forecast based Finance (FbF) is an example of an Early Action Plan (EAP) mechanism that enables disaster preparedness through humanitarian funding for early action based on in-depth forecast information and risk analysis. The release of funds to trigger early actions is agreed in advance and is based on forecasts exceeding specific thresholds (figure 5.6).

Figure 5.6: Early Action Plan (EAP) validation steps (Heinrich and Bailey, 2020).

1. Risk assessment. Historical impact reports are used to identify risks, however, there remains a lot of uncertainty about how events impact communities. Impact reports require a broad participatory process involving national meteorological services and disaster management agencies collaborating with government and communities to identify beneficiaries (Who is most vulnerable? Who will benefit the most?). Broad involvement is used to achieve collectively supported decisions.
2. Identify forecasts. Forecasts from local institutions are prioritised as they will have a mandate and early warning systems in place. Trust in and a sense of ownership of local forecasts can be more important than forecast skill.
3. Define impact level. When will we trigger? The funding can't support lots of false alarms so organizations aim to trigger only for high impact (1 in 5 years) events. Forecast skill may require accepting a certain number of false alarms or misses. It is important to collectively agree on an acceptable probability of false alarms and misses as these can degrade trust if the approach is not collectively owned. Collective agreement is difficult but is a core tenant of managing uncertainty in this context.
7. Multiple flexible triggers. Some uncertainty can be managed by using multiplied staged triggers. The first trigger has a higher false alarm rate but activates low cost preparedness actions. The second trigger has a lower false alarm rate and may even be a STOP for action. Flexible triggering moves away

from “objective” triggers and allows for expert consensus on triggering. This allows for unanticipated factors not captured by the trigger model to be included (e.g. emerging conflict).

Transparency and trust

Communication formats should **transparently** convey the nature of uncertainty being communicated and be readily comprehensible to ensure that decisions can be made based on an understanding of the uncertainties. Traditional, scientific formats for communicating uncertainty, such as technical graphs, can be difficult for non-scientists to comprehend. Although simplified information may be more easily understood, it may not provide sufficient depth of information to inform decisions. Finding the right balance may be best achieved using co-production (Coventry et al., 2019).

Trust in climate information and those who communicate information should be measured and evaluated to assess how communication and engagement activities influence trust in information. Stakeholders often equate uncertainty with ‘not knowing’ and/or a lack of accuracy. This can reduce trust in using the information and in turn prevent action. Measuring trust can help identify communication approaches that foster shared understandings of uncertainty (Coventry et al., 2019).

Climate risk narratives and storylines

There is strong evidence that people use narratives to capture the essential meaning of complex evidence (see also section 3). When presented with complexity, people gravitate towards constructing a narrative. Even if someone is presented with a scientific graph, what they take away will be a narrative about what the graph means, and that meaning will be different for different people. Just as risk is different for different people, the way they engage with complexity is different too. People also tend to hold on to existing narratives and seek evidence that confirms these (confirmation bias).

Figure 5.7: Understanding existing risk narratives and the co-creation of new climate risk narratives and adaptation pathways towards climate resilience for informal settlements in Lusaka, Zambia. Climate science information was presented during this process, such as flood maps from high resolution modelling, but it was available as print-outs on the walls and did not drive the narrative.

Collaboratively developing climate risk narratives or storylines begins by taking time to understand existing narratives within a particular decision context (figure 5.7). Until a climate communication practitioner understands existing narratives and how people are thinking about risk and decision making within these spaces it is very hard to introduce climate information. Once a practitioner has an idea of existing narratives, trust can be built through mutual learning, embracing the diversity and contradictions of people with competing views and understanding. Working with humility and transparency is needed to co-create new Climate Risk Narratives.

Climate scientists need to understand that they bring only one part of the information into a complex context. The climate component is not superior or dominant compared to other parts of the context. Therefore, scientists need to work collaboratively to decide how to interrogate the uncertainty of climate model projections and allow everyone to engage with the assumptions that are made. For instance, average rainfall changes were not considered to be the main concern for Lusaka and so were not included in the scenario analysis.

Many of the responses to the different climate risk scenarios were very similar (once the decision spaces and funding constraints had been worked through) (figure 5.8), so perceived uncertainty about what action to take to build resilience became clearer.

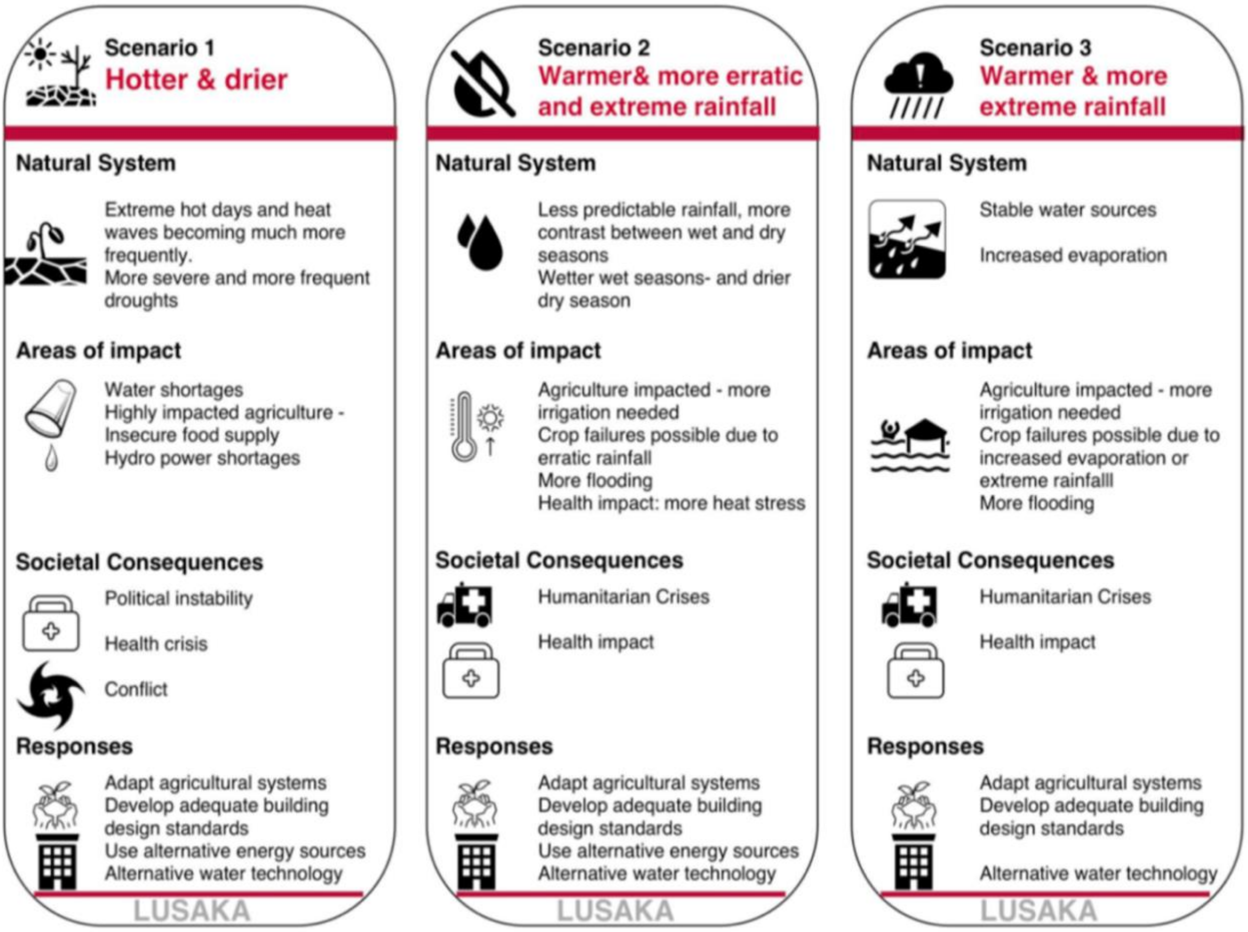

Figure 5.8: Climate Risk Narratives / Storylines for Lusaka, Zambia for three scenarios: 1. Hotter & drier, 2. Warmer & more erratic and extreme rainfall, 3. Warmer & more extreme rainfall.

Two strong pathways emerged: a strong engineering/planning pathway with a flood masterplan and large-scale drainage, and a separate pathway focused on local governance: who is involved in decision making? Local area development planning was followed up with financial resources to enable locally lead implementation.

The climate risk narrative/storylines process resulted in shifts in local climate governance. Ground-water recharge conservation areas were implemented. Finance was allocated to local ward development committees to address local climate risks (e.g. flooding) in ways that they felt were appropriate. And a community of practitioners was built that included city officials who were engaged in the decision making and had a positive impact.

Good decisions
Recognising that in general each decision maker has different demands –even those in the same geographical location and in the same sector, e.g. two farmers with adjacent plots planning to plant the same crop but considering different types of seeds-, "good" or "bad" decisions can mean completely different things.

Assuming that the demand has been correctly identified, and hence what is beneficial ("good") in order to satisfy that demand, at the end of the day "good" decisions are what is aimed for... But what are good decisions?

Any communication of climate information should be informed by an understanding of:

- How decisions (especially assumptions on the pathway from science to decision making) are really made and by who.
- How risk is already perceived and managed, heterogeneity is difficult to capture in risk models.
- What the implications of "bad" decisions are.

Climate communication is deeply entangled with trust, humility, mutual learning and contested perspectives. How to do this communication within a standardised approach of climate services in the face of contextual complexity and differing perspectives remains a challenge.

6 Concluding Comments: Emerging Themes

This section includes concluding remarks, in the form of key "emerging themes" or lessons learnt.

Start with the most relevant risks
An exploration of vulnerabilities can be used to discover which climate risks are of most concern. From there a climate communication practitioner or risk analysis facilitator (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.

Standard approach to uncertainty descriptions
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.

Use language the audience is familiar with (don't say uncertainty)
The vocabulary of science can have very different meanings in public life. Therefore, when dealing with climate services and decision makers, it is usually better to use commonly understood descriptive language in place of scientific terminology, along with multiple contextualised examples illustrating the concepts and approaches. Particular care should be taken with uncertainty communication, for instance, rather than using the word "uncertainty" which implies ignorance, a better choice could be the word "range", and rather than presenting a likelihood as a percentage instead refer to it using the framing of odds.

There are multiple ways to evaluate and communicate uncertainty
Decision makers require the best, reliable information to optimally accomplish their job. Although a measure of uncertainty must be always conveyed, there are multiple ways to measure and communicate it. The most used way is to communicate uncertainty via probabilities of occurrence (or not occurrence) of a certain event, but very often decision makers consider the use of odds -and relative odds- more understandable and actionable than actual probabilities. It is also possible to communicate uncertainty by a combination of the expected value (e.g. the ensemble median) and uncertainty bars (e.g. the ensemble interquartile range). In other contexts, it may be more appropriate not to communicate probabilistic information at all and instead explore the use of plausible storylines to help communicate climate risk and highlight specific vulnerabilities.

Use communication about uncertainty to build trust
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.

Precision of information should be relevant to the situation
General statements of uncertainty can be sufficient. Even if a quantitative analysis is possible it may not be necessary. The precision of a risk description should match what is needed. The presenting of

high resolution data will lead audiences to assume a high degree of certainty that may not be justified. Risk descriptions should match what the knowledge supports.

Understand existing narratives

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.

Be aware of deep uncertainties

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.

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