Enabling Climate Information Services for Europe

Report

User guide on uncertainties

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Summary

This deliverable report provides a guideline for users of the ECLISE project to deal with different types of uncertainty that are part of climate change projections. Understanding climate change uncertainty is important for decision making to prevent under- or over adaptation. Climate change uncertainty is, however, very complex and originates from different sources that are not all quantifiable. Moreover, the ratio of these sources change over temporal and spatial scales, which is important to consider when developing climate adaptation strategies for the future. A new framework is developed for this deliverable that shows the evolution of these different types of uncertainty over different time scales for the most important climate variables. Furthermore, the most important ways to assess uncertainties in climate change projections, quantitatively and qualitatively, are explained and a summary of existing methods to deal with uncertainty for the development of climate adaptation strategies is given.

Contents

1. Introduction

Warming of the climate system is unequivocal and global surface temperature change for the end of the century is likely to exceed 1.5°C (IPCC 2013). These changes will impact society from global to local scales. Two responses have emerged to deal with this issue: mitigation and adaptation. Mitigation (i.e. the reduction of greenhouse gas emissions and/or the enhancements of sinks) is the only response that can reduce the effects of climate change. However, even if stringent mitigation measures will be taken, it may take decades before the measures have an effect. Therefore, adaptation is the only response available for the impacts of the coming decades, and depending on the mitigating measures that are taken, are also likely to be necessary thereafter. Adaptation is the practice to cope with the impact of climate change. It is a process through which societies can better cope with an uncertain future. There are many strategies and measures to adapt, ranging from technological options, such as increased sea defence to behaviour change at the individual level, such as reducing water use. Often, however, adaptation requires costly investments. Adaptation can be more effective and less expensive when it includes an anticipatory component. Anticipating climate change is dependent on information about the direction and extent of change within a certain time frame. Moreover, pro-active decision-making about adaptation requires knowledge about the tolerance of society and acceptance of risk and the costs and benefits of different courses of action. Many of the elements are based on uncertain knowledge. Dealing with uncertainty in decision making is, however, not new; people constantly deal with uncertainties and probabilities. Uncertainty is thereby also not a unique characteristic of climate change. The unique challenge of climate change adaptation stems from the long time frame on which changes are considered, combined with the potential high risks and complexity of the uncertainties, which requires intensive collaboration between decision makers and scientists.

A wide range of information is available to support adaptation planning. Part of this information stems directly from climate models and provides knowledge on the global or regional changes in variables like temperature, precipitation and sea level. Other information sources are derived from impact assessments and give more applied knowledge on how climate change influences water quantity and quality or crop productivity. Each of these information sources is characterized by uncertainties. Some uncertainties are derived from a lack of knowledge, while other uncertainties stem from intrinsic variability in the climate, economic, social and environmental systems.

Making decisions in face of an uncertain future is a major challenge for policy makers and decision makers. Likewise, describing uncertainty presents a major challenge for scientists. Climate change uncertainties are very complex and need to be described in such a way that it assists decision makers to use the information in a productive manner. To provide the climate change information for the support of decision making, climate services are offered and developed. Climate services are based on scientific credible information and expertise, have or create engagement between users and providers, have an effective access mechanism and meet user's need (Hewitt et al. 2012). In the ECLISE project, local climate services are developed in close cooperation with users. The gaps that were described between the user demands and the information provided, were often tightly connected to uncertainties of climate change projections. The experience within the ECLISE project where users and providers worked in close-cooperation on the development of climate services to support climate adaptation policies has guided the development of this document on dealing with climate change uncertainties. The initial case study results revealed that the level of ability to cope with uncertainties varied substantially among different users and depends on their experience to work with climate information, but also on their willingness to take more than just one number into account. Therefore the advice given in this guidance about dealing with uncertainty is not a standard recipe for success. Each adaptation planning process had its own challenges and characteristics. Cooperation between policymakers, decision makers and scientists is a crucial elements. This cooperation is needed for effective communication of uncertainty, it provides flexibility that is needed to adapt to the specific characteristics of a case.

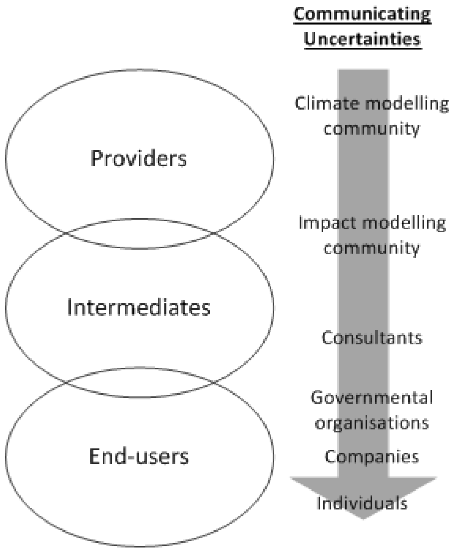


Figure 1: Communicating uncertainty through different levels.

The primary purpose of this guidance is to provide information for the intermediate level and informed end-users, as shown in Figure 1. This guidance will be most effective for readers with some prior knowledge on climate change and associated uncertainties. A lot of information is already available on dealing with climate change uncertainties, e.g. through the http://climate-adapt.eea.europa.eu website. Most of the available documentation explain the sources of climate change uncertainties and summarise the existing frameworks and approaches to deal with uncertainties. Some reports have developed a new framework to deal with risks and uncertainties or focus on one framework. Until now, not much has been written in these guidance's about the role of uncertainty in time and characteristics of uncertainties for different climate variables. This uncertainty guidance will, as part of the ECLISE project, mainly describe uncertainty for changes in Europe. The guidance starts with explaining the importance of uncertainty for decision making in section 2. In section 3 the different sources of uncertainty are described. The focus of this guidance is the presentation of a new framework in section 4 to evaluate the information that is provided on climate change uncertainties, given different time periods and climate variables. This framework allows users of documentation on climate change to evaluate quickly whether sufficient information is given on the range of uncertainty and to determine if it is necessary to seek additional information sources. In section 5 and 6, methods to assess and deal with uncertainty are discussed. This report ends with a final synthesis in section 7.

2. Why is uncertainty important for decision making?

Many decisions are only short-term and thereby often not or only partly climate sensitive. A farmer that wants to build an extra stable for its cattle, will not worry about climate change, as the stable will only last up to a few decades and climate conditions will not change drastically on this time scale. A lot of decisions also, however, require a long term commitment and are very climate sensitive. Examples of these decisions include infrastructure, drainage, energy production, building projects and water (risk) management. These decisions influence long time periods, up to 200 years.

The city of Rotterdam in the Netherlands, for example, is largely situated below sea level. The city is located along the banks of the Nieuwe Maas river, which is one of the branches of the delta formed by the river systems Rhine and Meuse. Climate change increases river discharge, sea level and the probability of storm surges. As the city continues to develop and expand, the development plans should incorporate these possible changes in order to provide a safe living and attractive economic environment. When, for example, more businesses are developed in areas that are below sea level, it is important that these areas will be safe from sea level rise. Dikes need to be reinforced, but the extent of this reinforcing depends on the extent of sea level rise. As reinforcing is a costly process, may take up a lot of space and requires a long term commitment, it is important that the decisions are robust, but not overly cautious. Therefore, uncertainties and assessing risk is an important part of decision making.

For the development of climate sensitive structures, like river dikes, often climate data are used. Climate data, for example, can be historical time series of river discharge, precipitation and temperature. Often these series are only up to periods of 100 years. To get insight into or better understand the probability of extreme events, statistics are applied and the 100 years' time series are extrapolated to provide information about the probability of a 1000 year event. Climate change may, however, change the statistics of these events. An event that currently is a 1000 year event, may be reduced to a 500 year event in 2050. Climate models are used to assess these changes in statistics of climate variables like temperature and precipitation. Climate models are based on the earth system and simulate the interactions between all the components of the climate system. Based on expected greenhouse gas emissions for the next century or more, scenarios are developed that are used as input to the climate models. The climate models can then simulate the climate for the next 100 years or even longer. These simulations show changes in variables like temperature and precipitation, but also of cloud cover, wind patterns and sea levels. The forecasts of the climate can support long term decision making and help policy and decision makers to decide whether *e.g.* a certain area should be available for construction and how robust this construction should be a to changes. There are, however, a number of challenges for decision making based on these projections, mainly relating to the uncertainty of climate change. One major challenge of projecting climate change is that they are not directly based on observations or experimental methods. And although the theory of the climate models is based on observational data, the climate models project a system outside the ranges of climate within those data were collected. There is no opportunity to reduce the uncertainties through observations. Other challenges include the speed on which the change occurs and the influence of known and unknown feedbacks in the climate system.

Decision making identifies and choose alternatives based on the values and preferences of the decision maker. When there is the comfort of relatively low uncertainty in combination with low stakes, than the application of cost benefit analysis and expected utility can be rather straightforward. When the uncertainty and stakes are high, however, the decision making environment is much more complex. In the complex and high uncertain context of climate change, conventional decision analysis may not be suitable.

When uncertainties are large, efforts can be made to reduce uncertainties through research. Also efforts can be made to understand the uncertainties better, so that they can be more confidently incorporated in the decision making process (Morgan 2009). In climate science both reducing and understanding uncertainties are important objectives. While eventually uncertainties in climate science will be reduced, the past decades of research have shown, that with increasing knowledge about the climate system, also new uncertainties were added, which resulted in an unchanged or even larger uncertainty range. Although the uncertainty range has not been reduced, there is also great value in learning that we knew less than we thought we did.

The fact that uncertainties are large, does not mean that risks are small. Both the magnitude of possible climate change impacts and the costs of delayed action can be very large (Smith and Stern 2011). Because of the large and complex uncertainties associated with climate change, risk analysis does not provide a guarantee that the climate risks are correctly defined and characterised and that the best decision is taken. Two types of adaptation decision errors can be made (Willows et al. 2003a):

- *Over- adaptation*: Too much weight or significance is placed on the need for adaptation. The results is that either the anticipated climate change is not observed over the lifetime of the decision or the changes that take place do not have the anticipated impact. Over-adaptation can also occur when other non-climate related risks are underestimated and have a larger impact than climate change.
- *Under-adaptation*: Too little weight or significance is placed on the need for adaptation. The decision maker fails to identify climate change as a relevant factor for the decision, or places too much importance on non-climate related risks.

Implementing decisions that result in over-adaptation can be regarded as a waste of resources. Neglecting to implement decisions that results in under-adaptation can pose huge risks to biological and human systems. Characterising and understanding the main and relevant uncertainties for a decision is therefore very important in order to avoid over- or under adaptation. Which uncertainties are important and relevant for the decision depends very much on the local context. Physical climate change impacts differ between locations, but also vulnerability and the way sectors are organized. Interactions between researchers and regional or local decision makers is therefore very important in order to prevent over- or under adaptation and to gain a shared knowledge on which uncertainties are most relevant for the adaptation decisions that are needed.

3. Sources of uncertainty in the projections of climate change

3.1 Sources of uncertainty

Basically, uncertainty in climate change information stems from two sources. The first source is the natural climate variability inherent in the climate system. Climate variability will always occur. It is the way climate fluctuates above or below a long term average. In some years, summers can be very hot, in other years they are cold. And even though there is a warming trend on average, we can still experience very cold winters or chilly summers. The second source stems from the limitation to our ability to model and understand the climate system. The climate system is very complex, and scientists do not have a complete understanding of how all the aspects of the atmosphere, land surface, oceans and ice components interact with each other. And even if the understanding would be complete, then it would still be very difficult to capture this understanding in mathematical equations that interact with each other in such a way that the real world is simulated. However, scientist do try to simulate the earth system with the current (and ever growing) knowledge and understanding. To do this, scientists use complex mathematical models that require the most powerful computers. And over the last decades, the number of processes and phenomena that has been included grows steadily, as does the spatial resolution. However, in spite of all this sophistication, the models remain a simulation of the real world and are thereby constraint by their ability to correctly capture and portray each of the processes that affect our climate. Summarizing, there is a lot of knowledge on the climate system, the climate is however very complex and our knowledge is far from complete. In addition, the chaotic nature of climate introduces large uncertainty. As the body of knowledge has been growing over the past decades, there is increasing confidence in the projected changes that likely for key climate variables such as temperature, sea-level rise and the risk of heat-waves and droughts (Climate-adapt).

In general, there is greater confidence in projections for larger regions than for specific locations, in temperature changes than in precipitation changes and in gradual changes in average conditions than in extremes weather events such as storms (Climate-adapt).

In the literature many distinctions between different types of uncertainties are made. Some are fairly basic, including two or three types of uncertainty. Others are more extensive and include a detailed description of a large number of uncertainties. Also a distinction can be made between scientific and social types and sources of uncertainty. This guidance distinguishes between three types of uncertainty (Dessai and Hulme 2004):

1. Natural climate variability (stochastic uncertainty)

Climate varies over seasons and years, instead of day-to-day like weather. Therefore, the variability is not as noticeable as weather variability. In some cases people are affected by the climate variability, as for example farmers in Australia are experiencing consecutive years of extreme drought. Common internal drivers of climate variability include El Nino and La Nina events, which are shifts of warm, tropical Pacific Ocean currents that effects temperature and precipitation in a large region around the equator. External drivers of climate variability include volcanic eruptions and sun spots. Climate variability occurs regardless of any human influence. This means that this uncertainty will also persist even if the forcings would be known and the models highly accurate (Kang et al. 2013). The uncertainty of natural climate variability can partly be addressed by running multiple simulations of a climate model, for which the initial atmospheric conditions are perturbed.

2. Incomplete knowledge (epistemic uncertainty)

Epistemic uncertainty arises from incomplete knowledge or understanding of a particular process. It is related to our ability to understand, measure and describe the system. This incomplete knowledge or understanding includes the functioning of the climate system and the response of the physical, chemical or biological system. It encompasses uncertainty due to limitations of insufficient data, measurement devices, systematic errors, extra- and interpolations, variability in time and space and the subjective choices that are needed to assess its nature and magnitude. Epistemic uncertainty is also part of climate modelling and includes missing or inadequately treated processes and uncertainty in numerical values of parameters (Walker et al. 2003). Epistemic uncertainty in climate models can be addressed by comparing different climate models. Thus type of uncertainty can be reduced by further research.

3. Scenario uncertainty

The projections of climate change are based on scenarios of future emissions of greenhouse gases and other pollutants that have in impact on the climate system, these scenarios are called emission scenarios. Also socio-economic scenarios are developed which describe how world population, economies, political structures and life style may evolve over the 21st century. Emission and socio-economic scenarios represent plausible descriptions of how the future might unfold. Many assumptions have to be made to develop these scenarios, and thereby they are a source of uncertainty for future climate change. Within the scenarios there is also a human reflexive uncertainty. This stems from the notion that humans are capable of reflecting critically on the implications of their behaviour. For example, when scientists state that the climate is changing, than humans can decide to adopt mitigating measures. Also observations of climate change can trigger human action. This behaviour of society influences the socio-economic and emission scenarios and is part of the uncertainty in these scenarios.

3.2 Uncertainty for different climate variables on different time scales

For most local decision- and policy makers, changes in temperature, precipitation, sea level and wind are of importance. Also, the influence of these variables on other processes can impact local society, through for example river discharge, or snow melt. The uncertainty of projecting changes in these climate variables is not similar and also the contribution of different sources of uncertainty can differ. Also, the relative importance of the three sources of uncertainty, as described in Section 3.1, varies with prediction lead time and with spatial and temporal averaging scale (Räisänen 2001). In general it can be said that uncertainty from internal or natural climate variability dominates on short timescales and model or scenario uncertainty dominates on longer time scales. Also, the contribution of internal climate variability is larger at smaller spatial scales, than for large geographical areas. Figure 2 shows how each source of uncertainty contributes to the total uncertainty for global decadal mean surface air temperature.

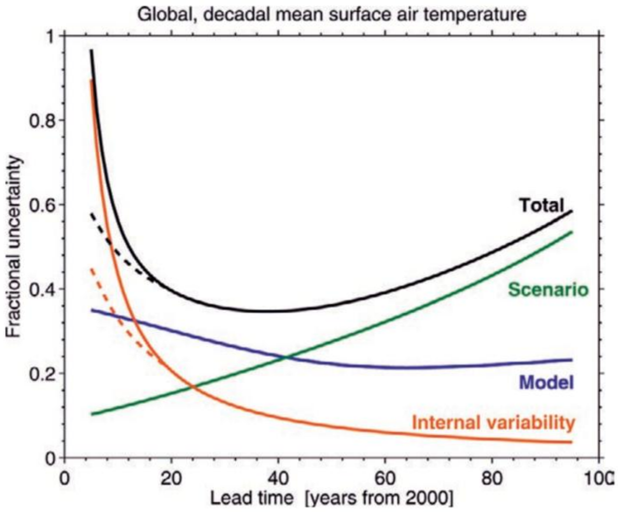


Figure 2: The relative importance of each source of uncertainty in decadal mean surface air temperature (Hawkins and Sutton 2009).

The contribution of different sources of uncertainty for global temperature as shown in Figure 2 will be different for other climate variables or more local regions. For example, for precipitation the role of internal variability is larger and the role of uncertainty due to scenario's is smaller. Also, for mean changes in variables the uncertainties are often less and distributed differently than for changes in extremes. To assess whether enough information is presented about uncertainties it is essential to have knowledge about the largest uncertainties and how these uncertainties are represented in the data or information provided. Therefore, in the next chapter, a model will be presented, that allows for an assessment of the climate data uncertainty.

4. A framework for the analysis of uncertainty

For decision- and policy makers it is important that they can assess relatively quickly if the information presented to them about climate change takes into account the most important uncertainties. Representing all uncertainties is impossible, because some uncertainties cannot be quantified, and it would also not be helpful for decision making as it would make the information too complex. As explained in the previous chapter, the relative importance of different sources of uncertainty vary over climate variables, space and lead time of the projection. In Figure 3, a framework is presented, which allows for a quick scan of data to assess whether the most important uncertainties are addressed.

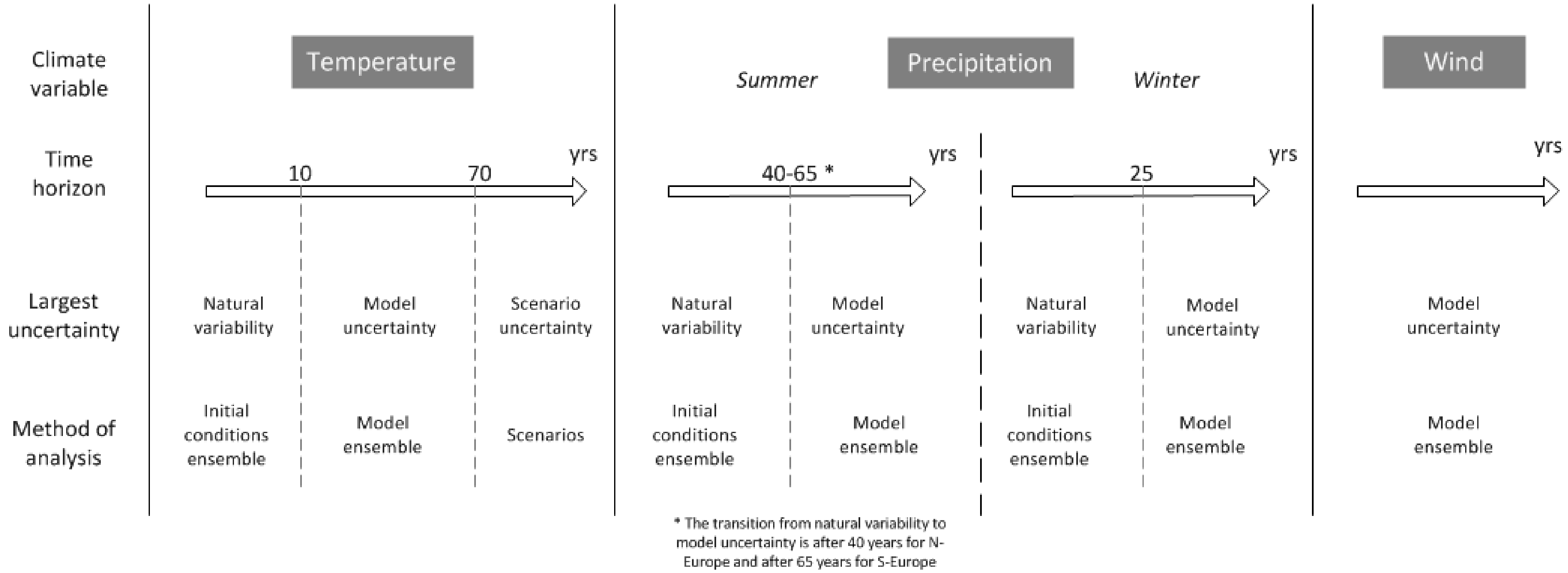


Figure 3: Framework to assess the most important sources of uncertainty (from: climate.ncas.ac.uk/research/uncertainty/maps.html). For temperature the years are based on a temporal 10 year meaning. The results show averages over Europe. Summer precipitation denotes the months June, July August. Winter precipitation denotes the months December, January, February. Please note that this assessment is made on results of global climate models, locally the uncertainties can be different. Often on local scales, initial conditions are more important (Prein et al. 2011).

Each component of the framework in Figure 3 is described below.

Temperature

Short term: Uncertainty in near term global climate change projections of temperature change is mainly dominated by internal or natural climate variability (IPCC 2013, see also Figure 2). For temperature change in Europe, this is true for the first decade of projections. The contribution of natural variability falls very rapidly with lead time as the climate signal strengthens (Cox and Stephenson 2007; Hawkins and Sutton 2009). But, on regional or local scales, the contribution of internal variability is considerably stronger (Hawkins and Sutton 2009).

Uncertainty due to natural climate variability can be assessed through historical observations. Long term temperature records show that the earth has known quite some variability. Records of the past 100 years give an indication of the current climate variability. To assess the contribution of natural climate variability to the total uncertainty of climate model projections of future temperature change, we need to assess the variability in the climate model simulations. One of the tools to assess this variability is to use large 'initial condition ensembles'. These ensembles are created by running one climate model multiple times with varying initial states of the atmosphere. Because the climate system is very chaotic, little changes in variables like temperature and wind in one place, can lead to very different paths for the system as a whole. Therefore, each ensemble member (of one model) has slightly different initial (start-up) conditions and thereby all members together give an estimate of the contribution of natural variability to the total uncertainty. Ensembles can be made for every climate model, the output of the ensembles will be different for each climate model because the models differ in their representation of natural variability.

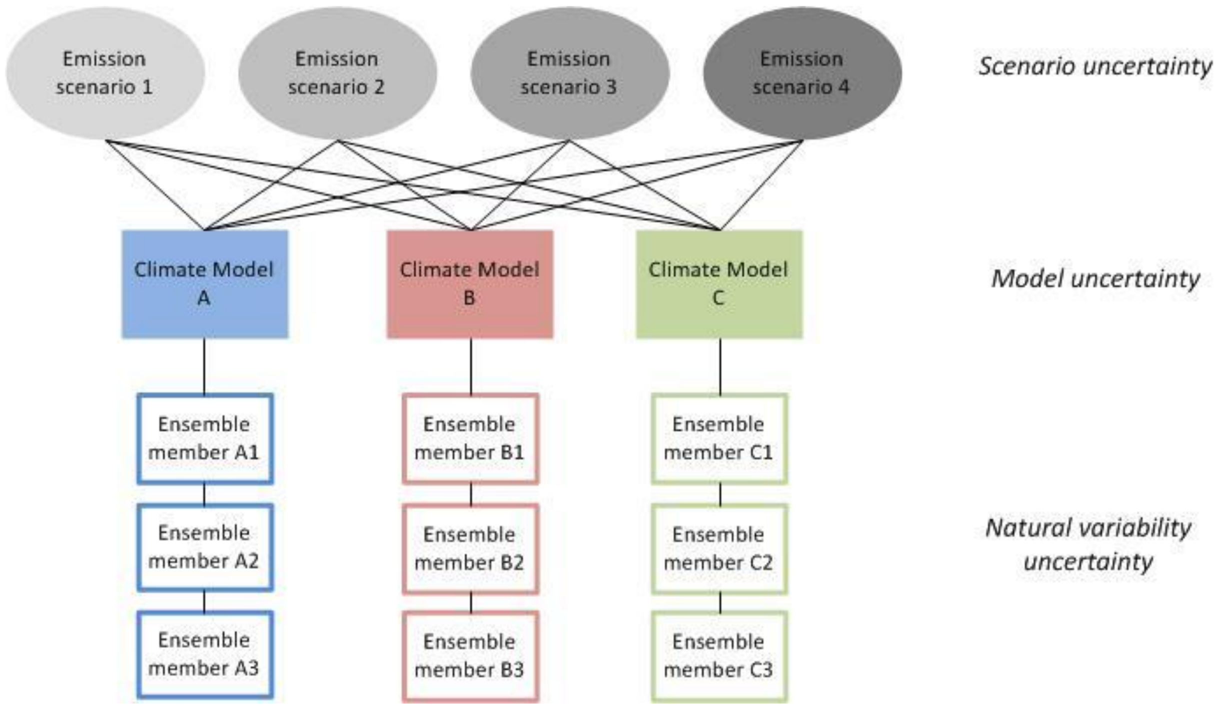


Figure 4: Different types of uncertainty in climate models and scenarios. The scenario uncertainty can be assessed by comparing the results of different emission scenarios. Model uncertainty stems from the different types of climate models that exist. Natural variability uncertainty can be assessed by using 'initial condition ensembles', which are created by running one model multiple times with different initial states of the atmosphere.

In Figure 4 the ensembles for each climate model are shown. The figure shows only three climate models (A, B, C) and for each model three ensembles members (e.g. A1, A2, A3), but in reality there are many more climate models and also often more ensemble members. Not each climate model has different ensemble members, however, some models only have one member due to the high costs associated with running a climate model. If it is possible, however, it is important to assess at least a number of these initial condition ensembles, as the representation of natural variability differs between climate models. Even though these ensembles can give us more insight in the contribution of uncertainty due to natural variability, the uncertainty due to natural variability is not reducible, therefore decadal projections will always be subject to large uncertainties (Smith et al. 2007).

Long term: after a decade, model uncertainty becomes most important. Model uncertainty increases with latitude, which is a likely consequence of differences in representations of climate feedback by the climate models (Hawkins and Sutton 2009). Model uncertainty can be assessed by comparing different climate model results, through multi-model ensembles. In Figure 4, the multi-model ensemble would be a combination of climate model A, B and C.

At the end of the century scenario uncertainty becomes dominant. It is, therefore, important to compare the results of different emission scenarios. However, not all climate models are driven by all emission scenario's, as shown in Figure 4. In reality, often the models are driven by a subsample of emission scenario's. Therefore it is sometimes difficult to assess the differences between emission scenario's using the same climate model.

Precipitation

Short term: Natural variability is a significantly more important factor for projections of precipitation change than for projections of temperature change (Räisänen 2001). Precipitation is more difficult to predict than temperature, and research has shown that projections of precipitation change are more consistent (i.e. higher signal-to-noise ratio) for some regions than for others (REFS see H&S). For the first 40 to 65 years, natural variability is the most important source of uncertainty for changes in precipitation, depending on the region of interest. This means that also changes in other impacts that are mainly driven by precipitation, like discharge of rainfall dominated river regimes, are mostly determined by natural variability. This result does, however, not mean that there is no climate change signal. It means that the uncertainty around the climate change signal can be mainly attributed to natural climate variability. Therefore to assess the uncertainty of changes in precipitation it is important to compare different 'initial condition' ensembles (i.e. model A1,A2,A3 in Figure 4).

Long term: For long term projections of precipitation, model uncertainty becomes dominant. Therefore it is important to assess the outputs of different climate models. Scenario uncertainty only plays a minor role for changes in precipitation over Europe. Therefore, the assessment of different emission scenarios is not really important.

Wind

The uncertainties for changes in wind are dominated by the climate models over the whole century. Scenario uncertainty becomes a bit more important towards the end of the century, but model uncertainty remains dominant (Prein et al. 2011). The relative contribution of natural climate variability decreases with height. Uncertainties in the winter season are larger than uncertainties in the summer season.

Downscaling

When results of climate models are compared, a distinction can be made between Global Climate Models (GCMs) and Regional Climate Models (RCMs). GCMs are large scale models, which need to be downscaled to give information relevant for the regional or local scale. Several methods exist to perform downscaling. Downscaling itself also adds uncertainty, for some variables this uncertainty is quite significant. The first method is called statistical downscaling. The purpose of statistical downscaling is to connect global scale predictions to regional dynamics to generate local climate projections. Statistical relationships are developed between large driving factors and local climate conditions, these relationships can then be used to project what might happen under different conditions projected by the GCMs. There is a variety of statistical downscaling methods, see (Schoof 2013) for an overview. A second method is called the delta change approach. This approach applies the change between a current and a future time series simulated by a GCM, and applies this change to an observational time series. If for example the mean change between the period 1971-2000 and the period 2071-2100 is 3 ^{o} C for the month January, than 3 ^{o}C is added to an observational time series in January. This is a very simple example of the delta change approach, but it is the basis of the method. For more information on this method see (Anandhi et al. 2011). A third method is to use RCMs, this approach is also called dynamical downscaling. A RCM is similar to a GCM, as it incorporates physics that describe the climate system. The difference between the RCM and the GCM is that the GCM simulates the climate system of the whole global earth, while the RCM only simulates a part of it on a higher resolution, e.g. an area like Europe. RCMs needs input at its boundaries from a GCM, this is called nesting. This also means that the errors of the GCM can be passed on to the RCM, or even enhanced by the RCM (for more information, see Feser et al. 2011). When model uncertainty is the largest source of uncertainty, global climate models can be compared, but for more local scales it is also meaningful to look at downscaled data, from RCMs or other downscaling techniques. It is important, however, to know that downscaling adds another source of uncertainty.

5. Methods for the assessment of uncertainty

Uncertainty analysis can be done in two general ways:

- Quantitatively, estimation in numerical terms of the magnitude of uncertainty
- Qualitatively, describing or categorising the main uncertainties

Quantitative analysis has advantages, because it enables an estimation of uncertainty, which propagates trough a chain of models. Quantification of uncertainty allows for specific bounds around the output of an assessment model. Numerous uncertainties can be assessed using different methods and are expressed by probability density functions or summary statistics (Scheraga et al. 2003). For a thorough quantification of the uncertainties related to climate change projections, an identification of all (critical) uncertainties is necessary, like uncertainties in model structures, parameters and inputs. However, climate change violates the postulates of quantification of all uncertainties, because it is associated with conditions of deep uncertainty (Lempert and Collins 2007). Deep uncertainty originates in the long time scales and complexity of climate change projections (Kandlikar et al. 2005) and it refers to social and scientific factors that are difficult to quantify. Not all sources related to climate change are quantifiable, therefore quantitative estimates may give an illusion of certainty. Qualitative approaches permit for an additional screening for potential biases and weaknesses in the analysis that cannot be captured by quantitative approaches (Scheraga et al. 2003). Words are used in qualitative assessments to describe the magnitude of potential consequences and to give meaning to quantitative outcomes. Qualitative assessments can e.g. reflect the judgement of a team of expert. The difference between quantitative and qualitative approaches can be rather fuzzy. For example, the IPCC AR5 report uses qualitative words to describe uncertainty. These words are, however, based on quantitative outcomes. Also, words like 'best estimate' can be coupled to certain model outputs, which gives a qualitative meaning to a numerical output.

5.1 Quantitative analysis

A mixture of methods exists to analyse uncertainty in climate change and the related impacts. For the quantification of uncertainty a key role is played by statistical methods and models. Examples of quantitative analysis methods are given in Table 1. Table 1 does not give an complete overview of all the methods, but it shows the main approaches used for the quantification of uncertainties.

Table 1: Quantitative techniques for uncertainty analysis (see also Refsgaard et al. 2007).

Type	**Description**	**Advantage**	**Disadvantage**	**More information**
Scenario analysis	Model output for trial values of input	Strong in statistical and scenario uncertainty	Ignores uncertainty in input and recognized ignorance or surprises	Katz (2002)
Sensitivity analysis	Partial derivative of model response with respect to output	Straightforward	Inadequate mechanism for determining uncertainty	Katz (2002)
Monte Carlo simulation analysis	Simulated distribution for output as function of input distribution	Formal probabilistic approach, very strong in statistical uncertainty	Computationally intensive, ignores other forms of uncertainty	Katz (2002)
Probabilistic multi-model ensembles	Numerous climate models run for common set of experiments	Strong in different types of uncertainty	Based on the ability of models to simulate the climate	Tebaldi & Knutti (2007)
Bayesian analysis	Using posterior distributions to determine probability distributions	Strong in statistical uncertainty	Ignores scenario uncertainty	Tebaldi, Smith, Nychka & Mearns (2005)

The quantitative methods shown in table 1 are mostly strong in dealing with statistical uncertainty, which is often derived from the models. The output of many of these methods depend on the ability of the climate models to simulate the 'real climate'. If an analysis shows that e.g. 80% of the models predict a temperature change between 2 and 3 degrees over Europe at the end of this century, than it does not translate directly into a 80% chance of this really happening. It means that in the simulated climate, there is a 80% chance of this specific temperature change. Also, when this kind of analysis is done, it is important to assess which variables have been taken into account. How many models have been used for the analysis, are different climate scenario's used, etc. Quantitative data output should always be evaluated in terms of accuracy and precision, which can be measures of reliability. Accuracy describes the ability of data, measurements or results to match the actual 'real' value. In the example of the climate models that simulate a temperature change between 2 and 3 degrees, the accuracy depends on the ability of the climate models to simulate the real climate. It relates to the difference between the true value and the probability density function (PDF) in question. The higher the difference, the lower the accuracy. The accuracy of climate predictions is always limited by fundamental and irreducible uncertainties (Dessai et al. 2009a). Precision is how close these data, measurements or results are to each other, working as a measure of the spread of data from the average (Adamson et al. 2014).

On the one hand extremely wide PDFs have low precision, it is difficult to assess what will happen from such a graph, but they may have a high accuracy. On the other hand, a narrow PDF may have a high precision, it shows higher chances of certain events that may happen, but they may have a low accuracy. In Figure 5 the difference between accuracy and precision is shown.

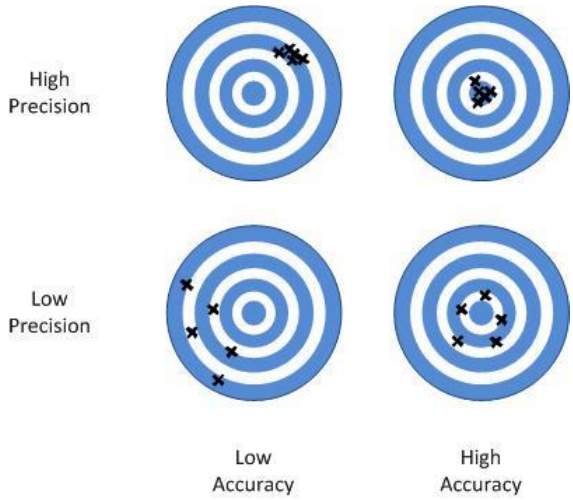


Figure 5: Visual examples of accuracy and precision, adapted from Adamson et al. (2014)

5.2 Qualitative analysis

There is a wide variety of words to describe various degrees of uncertainty: "likely", "probable", "possible", etc. The words all describe the probability of a certain (future) outcome. The IPCC calibrated words of likelihood against a series of descriptive terms. For example, the word "very likely" denotes a probability of 90-100%. This IPCC approach shows a mixture of qualitative words with quantitative estimates. As a results of the IPCC's choice for this semi-qualitative approach, there have been a number of studies on the effect of using the qualitative descriptions. A few risks have been identified (Budescu et al. 2012; Morgan 2009; Patt and Dessai 2005):

- The same words mean different things to different people
- The same words can mean different things to the same people in different contexts
- Important differences in experts' judgements about mechanisms (functional relationships) and how well key coefficients are known, can be masked in qualitative discussions

These risks show the importance of communication, but also of a combination of approaches.

Table 2: Examples of qualitative analysis of uncertainty

Type	Description	Advantage	Disadvantage	More information
Scenario analysis	Qualitative 'storylines' about logical and internally consistent events	Many different worlds can be described (extremes)	Difficult to test underlying assumptions	Refsgaard et al. (2007)
Stakeholder involvement	Assessment of climate change in decision making and modelling process with multiple stakeholders	Increases level of public accountability	High degree of subjectivity, can take a lot of time	J. Van der Sluijs et al. (2004)
Expert elicitation	Structured process to elicit subjective judgements from experts	Can include a wide array of knowledge, including sceptics	Fraction of experts holding a view is not proportional to probability	J. Van der Sluijs et al. (2004)
Quality Checklist	An instrument to assist modellers and users of modellers in the process of model quality control	It shows where problems with regard to quality and uncertainty may occur	It does not solve the problem of the validation of climate models	J. Van der Sluijs et al. (2004)

Quantitative techniques are essential in uncertainty analysis, but they can only account for what can be quantified in a credible way. Moreover, they can only address the technical dimension of climate change. Qualitative approach can complement the quantitative approaches , which allow for an assessment of uncertainties that are hard or impossible to quantify (Van Der Sluijs et al. 2005).

6. Tools and methods to deal with uncertainty for decision making

When confronted with climate change uncertainty, a first reaction can be to wait until the uncertainty is reduced and scientific knowledge and understanding are improved. It is much easier to develop adaptation options based on reliable future climate forecasts. It is logical to assume that when sciences progresses, the range of projections will narrow and uncertainty will be reduced. Uncertainty, however, has not been reduced in the past decades. Yes, science has produced much more knowledge and understanding of the climate system. But, as scientists learn more about the climate system, they also learn more about the things we cannot estimate accurately and precise yet. This knowledge about the things we do not know, increases the uncertainty range. Also, uncertainty will never completely disappear, as there are conditions of deep uncertainty, i.e. the future can never be completely predicted. We cannot precisely predict, for example, human action. And also natural climate variability causes uncertainty that cannot be reduced. Therefore, the development of climate change adaptation strategies should not be hindered by uncertainty.

Different approaches are developed to deal with uncertainty in adaptation planning. Unfortunately no general framework exists to select a particular planning approach (Climate-adapt). Choosing the right approach that will help to manage the risk and uncertainty for the situation at hand can be difficult. It is, however, important to compare the different approaches and to think about the best option, because the decision-making frameworks can provide a systematic approach to manage uncertainty and to choose from a multitude of adaptation options (Randall et al. 2012). In this guidance, a few frameworks are selected that demonstrate how different frameworks deal with uncertainty in decision making. In general, two important factors decide on what approach to use: the level of climate change uncertainty and how controllable the system is for which a decision needs to be taken. Figure 7 shows how those two variables relate to each other and which type of decision frameworks matches which situation the best. Below the different approaches are described with examples of frameworks.

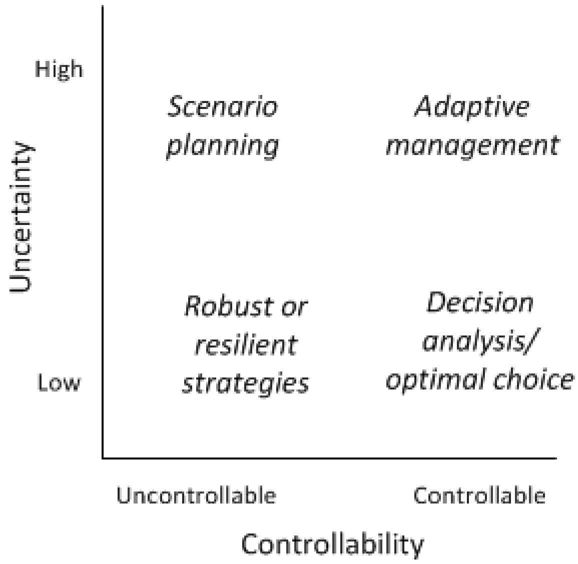


Figure 7: The level of climate change uncertainty and controllability of the system are important factors in determining which decision framework fits best, adapted from Allen & Gunderson (2011)). Together they form four complementary approaches for adaptation planning.

6.1 Scenario planning

When uncertainties are high, and the system is rather uncontrollable, than scenario planning is a good tool for decision making. Scenarios have stood at the heart of projections of climate change, which were driven by socio-economic scenarios of the future. They are a powerful way of representing uncertainties in complex and dynamic systems (Berkhout et al. 2013). Scenarios can account for many different outcomes, e.g. the worst extremes. It allows the decision maker to consider different plausible outcomes through scenarios which represent different future states of the world. Decision analysis is then undertaken to compare how well alternative policy decision perform under these variety of future conditions (Climate-adapt). A range of scenario approaches are available to address different decision making contexts. The scenarios can be developed for different time scales. For example, near-term and simple scenarios: "what will we do if next summer gets very dry", to long-term and complex: "what will happen if precipitation extremes increase a lot, but there is almost no water management budget". Scenario's take into account the trends in the past from observations. Scenario planning can be used as a stand-alone brainstorming process, but also as part of an established planning process (Moore et al. 2013). Scenario planning can be approached either top-down or bottom-up (Dessai and Hulme 2004).

The top-down approach, also known as the 'predict-then-act' approach focusses on downscaled global climate change scenarios and is strong in dealing with statistical uncertainty. For this approach one or more climate scenarios are used as starting point for an impact assessment. The goal is to derive an optimal adaptation strategy, based on the results of the impact assessment. The solution that is found, performs best contingent on a particular view (Lempert and Collins 2007). This approach is the traditional approach that has been used by the IPCC and is also part of the UKCP uncertainty guidance (Willows et al. 2003b). The steps usually involve (Dessai et al. 2009b):

1. Identify and structure the problem using scenarios
2. Characterize uncertainty and assess risk
3. Identify and appraise options
4. Conduct sensitivity analysis
5. Suggest optimum alternative

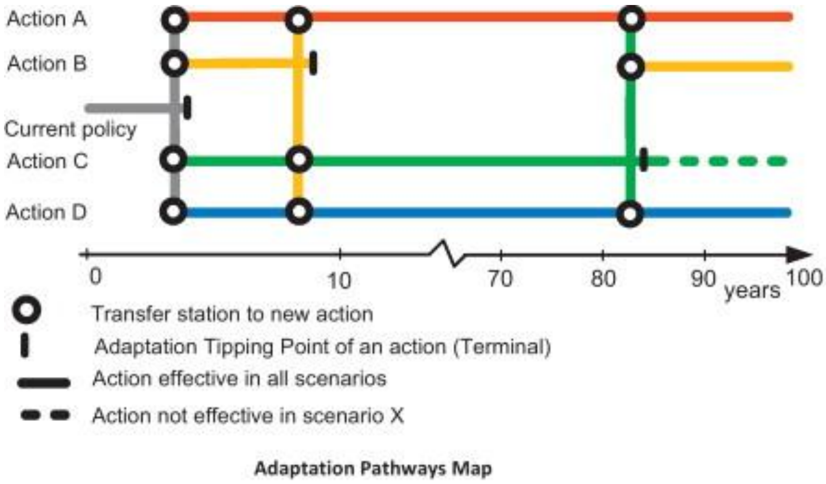
A bottom-up scenario approach or 'assess-risk-of-policy' framework does not take the climate change scenarios as starting point, but rather the vulnerability of the physical, biological and/or social system. It also takes into account the development, ambitions and resilience of the system into account. Resilience can be defined as the ability of the system to absorb disturbances (Aerts and Droogers 2009). An example of a bottom-up scenario approach is the adaptation tipping point analysis (ATP). In this approach, the focus is on tipping points in local or regional adaptation strategies. At a tipping point, the current management or policy objective does not suffice anymore (Kwadijk et al. 2010). Usually the following steps are involved:

1. Identify and structure problem
2. Propose one or more strategies
3. Assess each strategy over a wide range of scenarios
4. Summarize key trade-offs among promising strategies
5. Suggest robust alternative

Scenario planning allows for the involvement and interaction of diverse stakeholders to develop a shared understanding of risk, trade-offs and possible adaptation strategies. Scenario planning allows scientists and policymakers to think about plausible futures, but also about extreme or worst case scenarios. It thereby is a flexible approach, which can incorporate different time horizons and different expert levels of input.

6.2 Adaptive management

When uncertainties are high but the system is controllable than there is a lot of potential for learning than adaptive management functions best. It involves the selection of a strategy that can be modified to achieve a better performance as one learns more about the issues at hand and how the future is unfolding (Climate-adapt). The approach aims at learning from outcomes and should be flexible enough to adapt to these learning outcomes. Thereby a key feature of this approach is that it ables decision makers to seek strategies that can be modified as the future unfolds. Examples of adaptive management are the dynamic adaptive policy pathways, which is a theoretical approach describing a planning process with different types of actions and signposts to monitor and see if adaptation is needed (Haasnoot et al. 2013). A graphical summary of this procedure is given in Figure 8.



	Path actions	Relative Costs	Target effects	Side effects
1		+++	+	0
2		+++++	0	0
3		+++	0	0
4		+++	0	0
5		0	0	-
6		++++	0	-
7		+++	0	-
8		+	+	- - -
9		++	+	- - -

Scorecard pathways

Figure 8: An example of Adaptation pathways and a scorecard presenting the costs and benefits of the 9 possible pathways presented in the map. In the map, starting from the current situation, targets begin to be missed after four years. Following the grey lines of the current policy, one can see that there are four options. Actions A and D should be able to achieve the targets for the next 100 years in all climate scenarios. If Action B is chosen after the first four years, a tipping point is reached within about five years; a shift to one of the other three actions will then be needed to achieve the targets (follow the orange lines). If Action C is chosen after the first four years, a shift to Action A, B, or D will be needed in the case of Scenario X (follow the solid green lines). In all other scenarios, the targets will be achieved for the next 100 years (the dashed green line). The colours in the scorecard refer the actions A (red), B (orange), C (green), and D (blue) (Haasnoot et al. 2013).

An important element of the adaptive management approach is that the decision time scale is such that incremental adaptation is possible and decisions can be updated as new information becomes available. Another example of adaptive management is Thames Estuary 2100 project. London and the Thames Estuary have always been subject to flood risk. The Thames Barrier is one of the iconic features of the current flood risk scheme. This barrier however, was not designed to account for the sea level rise of the 21st century. Therefore, the Environment Agency set up the Thames 2100 project to keep the hinterlands safe from sea level rise for the next 100 years. The outcome of the project was a set of adaptation options linked to different extents of climate change. Each option consists of an decision pathway through the century to deal with different sea level rises. Planning decision lead times and consequence times created challenges, which were also explicitly addressed, with the timing of key decision points along the trajectory (Smith et al. 2011). For more information on this project see also (TE2100 2012).

6.3 Robust or resilient strategies

When the uncertainties are not large, but the system is not very well controllable, than robust or resilient strategies can perform well. A robust strategy performs well over a wide range of futures. However, often the range of these futures cannot be too wide, otherwise it is very difficult to find a strategy that is robust. Therefore, the uncertainties should not be too large. This can work for climate change, especially on smaller time scales and for variables that are less uncertain like temperature (instead of i.e. precipitation). Of course when uncertainties are high, strategies can also be designed that increase the robustness of resilience of a system, but the strategies itself might not be robust or resilient over a wide range of plausible futures. There is some difference between robust and resilient strategies.

Robust strategies

The IPCC (2013) has identified robustness as strength or degree to which a system is not given to influence. Robustness analysis systematically explores the uncertainty space, which is defined by plausible range of futures, to find out were in that space an option works or fails. A fully robust option would work in the entire uncertainty space. The approach can be applied when traditional risk information is not available, when there is no agreement on which conceptual models to use, or how to evaluate alternative outcomes (Watkiss and Dynzynski 2013). A comprehensive, formal application of the approach was undertaken by Lempert and Groves (2010). In collaboration with stakeholders it selected key performance measures like annual water demand and cost of supply and then developed alternative management strategies. The study then identified significant uncertainties ranging from climate change to the achievement of management strategies. A model was used to evaluate the performance of the strategies across different scenarios. Then key trade-offs between the strategies were summarized and robust alternative strategies were suggested to the stakeholders (see also Watkiss and Dynzynski 2013).

Resilient strategies

A resilient system can withstand shocks and extreme events and then return to its original state. Resilience can be found in physical and biological systems, but also in social systems. Resilience in social systems includes the capacity of humans to anticipate and plan for the future and to adapt to events that were not anticipated. As the physical, biological and social system are tightly interconnected, the resilience is often determined by the response of the total system to changes. Resilience has three characteristics (www. resalliance.org):

- The amount of change a system can undergo and still retain the same controls on function and structure (including shocks)
- The degree to which a system is capable of self-organisation
- The ability to build and increase capacity for learning and adaptation

Ultimately the aim of resilient management is to keep the system within a particular configuration of states, that will continue to function as desired or to move from a less desirable regime to a more desirable regime.

6.4 Decision analysis or optimal choice

When the conditions of the system can be controlled very well and the uncertainties are low, than a decision analysis framework can be applied. This is rarely the case for making decisions for adaptation of climate change. Decision analysis uses quantitative techniques to identify the 'best' choice among a range of alternative management strategies. Model-based decision analysis tools are often used as part of interactive techniques with stakeholders. The treatment of uncertainty in decision analysis can be quite powerful, but the probabilities of the decision outcomes must be quantifiable. In climate change, objective probabilities have not been established for many outcomes (IPCC 2007). A well-known example of decision analysis is the cost benefit analysis (CBA). Simplified, CBA compares the net benefits of alternative adaptation strategies with a climate change scenario, taking into account all the costs and benefits for society as a whole. CBA prescribes choosing the alternative with the highest net benefit, evaluated in monetary terms (Randall et al. 2012).

6.5 Types of decision strategies

The decision frameworks as described above can result in different adaptation strategies, which include uncertainty in different ways. Often a combination of these strategies can be very effective in reducing the vulnerability of human an natural systems against climate change.

No-regret strategies

No-regret strategies are in most cases low-regret strategies, as it is difficult to guarantee that an option will be beneficial no matter what the future will be. The ‘no-regret’ type of strategy yields benefits even in case of little or no climate change (Hallegatte 2009). For example, implementing more efficient ways of irrigation in dry areas is beneficial from a cost-benefit point of view even without climate change. However, in other regions, which now have an abundance of water, the costs of the strategy do not outweigh the benefits in the current climate. The costs are only justifiable if there is a considerable decrease in precipitation in the future climate. Irrigation can be a no-regret strategy in some regions, but in other regions it is a strategy that should be considered carefully among multiple futures to assess if it is worth the investment.

Other examples of ‘no-regret’ strategies are insulation of buildings or houses, as this also saves costs of energy, reforestation, as it also improves the environment and can attract e.g. eco-tourism, the development of an early warning system, which can also be beneficial in the current climate or diversification of crops, which can also reduce the chance on crop disease.

Safety margin strategies

In the design of dikes it is common practice to apply an engineering safety margin on top of the design flood level in order to compensate for physical processes that have not been taken up in the design, such as overtopping of waves. This is a very conservative type of design (Dessai and Van der Sluis 2007). If the strategy is based on a worst case climate change scenario, than adding the safety margin would reduce the vulnerability to almost zero. However, the investments of such strategies can be very high. But, in some cases it can be the best option, especially for long term investments of large systems, such as the design of a sewerage system. It is very expensive and difficult to modify this system when it is not yet at the end of its lifetime. The costs of building this system for a bigger capacity are small compared to its total costs. Adding a safety margin is often a good option for strategies that are not so flexible or irreversible. Also when the costs are low for adding a safety margin it can be a good way to reduce the vulnerability to climate change.

Reversible strategies

The aim for this type of strategy is to keep the costs of being wrong about climate change as low as possible (Hallegatte 2009). The idea is that the development of the strategy can be changed or stopped when new information comes available. This type of strategy works well within the adaptive management framework. It takes uncertainty into account by anticipating the possibility that the future can turn out different than expected (Dessai and Van der Sluis 2007). An example of such a flexible strategy is the development of dikes that can be adjusted in time, because their design allows for an easy heightening or broadening and the spatial reservations for these adjustments have also been made already (e.g. van Loon-Steensma and Vellinga 2013). Another example is urbanisation. One can decide to not urbanise certain areas that are in flood risk zones. When, however, new information shows that these areas are quite safe, or when flood risk measures are improved, than this decision can be reversed.

Reduction of time horizons

Some long term decision can be turned into short term strategies. It is a form of adaptive management that only chooses decisions that are short lived, so that after a period of time there will be the possibility of designing a new strategy based on the most recent climate change information (Hallegatte 2009). Examples of these type of strategies are investment in an early warning system, in replacement for investments in other flood protection measures that are more expensive and less flexible like dikes.

Soft strategies

Climate adaptation strategies are not only about technical solutions. Soft adaptation seeks to decrease the sensitivity and increase the adaptive capacity of human and natural systems to build resilience. These actions are often less resource-intensive and may provide multiple benefits (Climate-adapt). Therefore, the strategies often also belong to the no-regret strategies. It also can include re-allocation of resources, behaviour change, institutional and/or sectoral reform/restructering, awareness raising, risk spreading via financial instruments, land use planning and spatial planning (Climate-adapt ; Wilby and Dessai 2010). For example, risk spreading via financial instruments can be achieved to insurances. A farmer can adopt an insurance scheme that protects the farm against heavy losses when weather is unfavourable. Another example of a soft measure is to develop better information services for disaster management. When a flooding is expected, than casualties can be reduced if people are well aware of the evacuation plan. Another example is the monitoring of emerging insect vector borne diseases in combination with campaigns and educational activities this can prevent an outbreak.

7. Synthesis

Attempts to achieve more consistency in the treatment and reporting of uncertainty by researchers is receiving more and more attention. Also frameworks and guidelines to deal with uncertainty are published increasingly. This ECLISE uncertainty guideline has described the main uncertainties in climate change that are important for decision making. It also provided a new framework which summarizes the uncertainties that are most important for different climate variables and timelines in Europe. For temperature, natural climate variability is the largest uncertainty for short term periods up to 10 years, while for precipitation natural climate variability is the largest uncertainty for periods up to 65 years, depending on the season and region. For wind, model uncertainty is the most important uncertainty throughout the coming century. Each type of uncertainty can be analysed with different tools, which are also described in the framework. The framework, thereby, allows for a quick assessment of the main uncertainties and can support the evaluation of data or information on climate change. The framework helps to identify if the main uncertainties are well described. In addition several methods to assess uncertainties quantitatively or qualitatively are presented. Finally different decision making frameworks and possible adaptation strategies are described which each deal with uncertainty in different manners. This guideline gives a broad overview of climate change uncertainty and ways to assess and deal with uncertainty. It also shows that there is not one best solution for all situations, every case requires different assessment methods and often a combination of strategies will be needed to increase the robustness of the human and or biological system.

Projecting climate change is very complex, because there are so many components involved. This includes a certain amount of chance related to natural climate variability, which is an uncertainty element which cannot be reduced. Quantification of uncertainties can be very helpful for risk assessments, which can guide a policy maker in the development of adaptation strategies that reduce risk. However, it is not possible to describe all the uncertainties quantitatively. Therefore a quantitative assessment of uncertainties will not describe the full uncertainty distribution. Furthermore, decisions under climate change uncertainty are not limited to mathematical and theoretical problems that only can be solved by the research community. Decision makers and stake-holders at different levels need to be involved, as knowledge about local vulnerabilities and other factors that influence the robustness of a system need to be taken into account. Also other types of uncertainty can be important in the decision making process. An argument also made by Koppenjan and Klijn (2004), who state that in addition to substantive uncertainty, which describes uncertainty in the scientific information about climate change, two other sources of uncertainty are important. First, strategic uncertainty, which is uncertainty about the strategic behaviour of actors in the decision making process, and second, institutional uncertainty, which denotes uncertainty about the differences in institutional backgrounds. This guideline has focussed on substantive uncertainty but in the decision making process also these other uncertainty will play a role.

Decision making under climate change uncertainty poses large challenges, especially for local climate services, as the spatial scale is small and often also the time horizon. This translates in even larger uncertainties. The main value of future climate projections is therefore mainly in learning us about the climate system and climate sensitivities and using this knowledge to determine if weather patterns are changing and to show these changes as trends in time series of climate variables. To estimate however, if the projected trends are accurate, it is necessary to have some knowledge about the most important uncertainties. This guideline shows which uncertainties are most important for different climate variables and different time periods and thereby allows the user of climate change information to assess whether the provided information gives enough insight into the climate change uncertainties.

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