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Chapter 2: Integrated Risk and Uncertainty Assessment of Climate Change Response Policies

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1 Executive summary

2 [Note from the TSU: for the Second Order Draft, key statements will need to be qualified by using
3 the IPCC calibrated uncertainty language]

4 This chapter is concerned with how to interpret and deal with risk and uncertainty in developing and
5 implementing policies and decisions aimed at reducing the impact of climate change. Uncertainty in
6 the Earth's climate system and the effect of greenhouse gas (GHG) emissions are core issues and
7 concerns at all levels of decision-making. Risk and uncertainty impacts on how individuals, groups,
8 and organizations process information and make choices under conditions of risk and uncertainty
9 and how they react to specific policy interventions. Risk and uncertainty impact on how policy
10 makers make collective choices at the local, national and international levels to deal with climate
11 change. Uncertainties are also inherent in the impact of policies aimed at mitigating and adapting to
12 climate change.

13 This chapter focuses on the nature of the risks and uncertainties associated with climate change,
14 how individuals and collective units perceive risk and make decisions in the face of this uncertainty
15 (descriptive analysis) and the tools and approaches that have been employed to improve the choice
16 process (normative analysis). Based on this descriptive and normative analysis we describe the
17 challenges that exist in managing climate change and its impacts through mitigation and adaptation
18 policies in the face of risk and uncertainty. The chapter examines interconnections between the
19 following elements:

- 20 • The decision to be made
- 21 • Key uncertainties and risks that matter for climate policy
- 22 • Risk perception and behavioural responses to risk and uncertainty
- 23 • Decision tools for making choices under risk and uncertainty
- 24 • Risk and uncertainty in climate change policy issues

25 **The decision to be made.** One needs to specify a set of alternatives and the accompanying risk and
26 uncertainty in making choices between them. For example, a farmer making decisions on what crops
27 to plant should concern himself with the likelihood and consequences of insufficient rainfall during
28 the next growing season and the uncertainties surrounding such seasonal forecasts. A community
29 determining whether to invest in an irrigation system to deal with the potential consequences of
30 drought has a much longer time horizon to consider and should utilize different climate change
31 scenarios in making this decision. A government implementing a carbon tax needs to be concerned
32 with the uncertainties associated with its ability to monitor firms' activities and the impact of a
33 specific penalty on firms' actions. A national government determining its position on negotiating an
34 international climate agreement on mitigation needs to concern itself with current and future global
35 climate change scenarios and the costs and benefits associated with specific mitigation and
36 adaptation investments.

37 **Key uncertainties and risks that matter for climate policy.** To develop effective and efficient
38 mitigation and adaptation policies, one needs to characterize the nature of the risk and uncertainty
39 associated with policies and decisions that reduce the negative impacts of climate change. The
40 farmer will want to understand the risks and uncertainties of drought in the future and its
41 consequences, given different technologies, programs and policies in place. Communities concerned
42 with developing irrigation systems will want to have an understanding of the drought risk should
43 specific investments be undertaken. Similarly, a government implementing a carbon tax will want to
44 evaluate how its implementation will impact on greenhouse gas (GHG) emissions and the impact of
45 these emissions on the likelihood of different climate change scenarios. Finally, delegates to the

1 Conference of the Parties (COP) will need to understand the benefits, risks and costs of different
2 ways to mitigate climate change and their inherent uncertainties. Risk and uncertainty impact the
3 construction of scenarios and evaluation of policy instruments for mitigating climate change and the
4 climate governance process.

5 **Risk Perception and behavioural responses to risk and uncertainty.** There is a large literature
6 demonstrating that individuals, small groups and organizations often do not make decisions in the
7 analytic or rational way envisioned by normative models of choice in the economics and
8 management science literature. Risks frequently are perceived in ways that differ from expert
9 judgments. Decision makers tend to be highly myopic and utilize simplified heuristics in choosing
10 between alternatives. To illustrate, farmers may perceive the likelihood of drought to be below their
11 threshold level of concern, even though the risk can be significant, especially over time. A coastal
12 village may decide not to undertake measures for reducing future flood risks due to sea level rise
13 because they focus on the next few years. They conclude that the expected short-term benefits do
14 not justify undertaking protection actions even though the long-term discounted benefits greatly
15 exceed the upfront investment costs of the proposed adaptation measures. Firms may not reduce
16 their emissions if the government imposes a carbon tax because they feel that they will not be
17 forced to pay a penalty because the regulation will not be well enforced. Government instructions to
18 national delegates may be based on the perception that the voting public has a myopic view of
19 climate change.

20 There is empirical evidence that individuals' perception of the likelihood of an event (e.g.,
21 availability, learning from personal experience), and emotional, social and cultural factors influence
22 the perception of climate change risks. Individuals also utilize different mental models in making
23 decisions. Different forms of risk communication are needed to overcome individuals' myopia and
24 impatience with respect to the risk and uncertainties of climate change.

25 **Decision tools for making better choices.** A wide range of tools have been developed for evaluating
26 alternative options and making choices in a systematic manner when probabilities and/or outcomes
27 are uncertain. The appropriate use of these models depends on the nature of the decision and how
28 the key stakeholders deal with uncertain information. Farmers and firms may find the expected
29 utility model or decision analysis as useful tools for evaluating different alternatives under risk and
30 uncertainty when an analyst demonstrates how these models can reduce their costs and/or increase
31 their profits. Communities deciding on whether to invest in irrigation systems that improve the
32 welfare of their farmers may find cost-effectiveness analysis a useful decision aid, while
33 governments debating the merits of a carbon tax may turn to cost-benefit analysis. Integrated
34 assessment models may prove useful to delegates intent on justifying the positions of their
35 governments.

36 There are a variety of tools and methodologies for analysing risk and uncertainty when individuals
37 are making choices for themselves and when decision-makers are responsible for actions that affect
38 both themselves and others (i.e. social choices). These tools encompass expected utility theory, the
39 use of integrative assessment models (IAM) in combination with cost-benefit and cost-effectiveness
40 analysis, adaptive management, robust decision making and uncertainty analysis techniques such as
41 structured expert judgment and scenario analysis.

42 **Risk and uncertainty in climate change policy issues.** Policies should take into account risk
43 perception and behavioural responses to information and data while at the same time utilizing the
44 tools and methodologies for improving decisions related to uncertainty and risk. The outcomes of
45 particular options, in terms of their efficiency or equity, are sensitive to risks and uncertainties. We
46 start with decisions at the broadest possible geographical and temporal scales, namely the selection
47 of long-term global greenhouse gas emissions and concentration targets and stabilization pathways
48 for dealing with uncertainty from the social planner's perspective and the structuring of
49 international negotiations and paths to reach agreement. The chapter examines strategies for

1 gaining public support for adaptation and mitigation policies at various levels of governance as well
2 as making the adoption of technologies more attractive economically under conditions of risk and
3 uncertainty. These include pathways to achieve pre-selected targets, the specific instruments and
4 interventions designed to do so, and the effects of risk and uncertainty on private sector
5 investments of many kinds.

6 2.1 Introduction

7 This chapter is concerned with how to interpret and deal with risk and uncertainty in developing and
8 implementing policies and decisions aimed at reducing the impact of climate change. Uncertainty in
9 the Earth's climate system and the effect of greenhouse gas (GHG) emissions are core issues and
10 concerns at all levels of decision-making. Risk and uncertainty impacts on how individuals, groups,
11 and organizations process information and make choices under conditions of risk and uncertainty
12 and how they react to specific policy interventions. Risk and uncertainty impact on how policy
13 makers make collective choices at the local, national and international levels to deal with climate
14 change. Uncertainties are also inherent in the impact of policies aimed at mitigating and adapting to
15 climate change.

16 The following examples highlight the types of decisions made at the individual, firm, regional, public
17 sector, national and global levels of analysis:

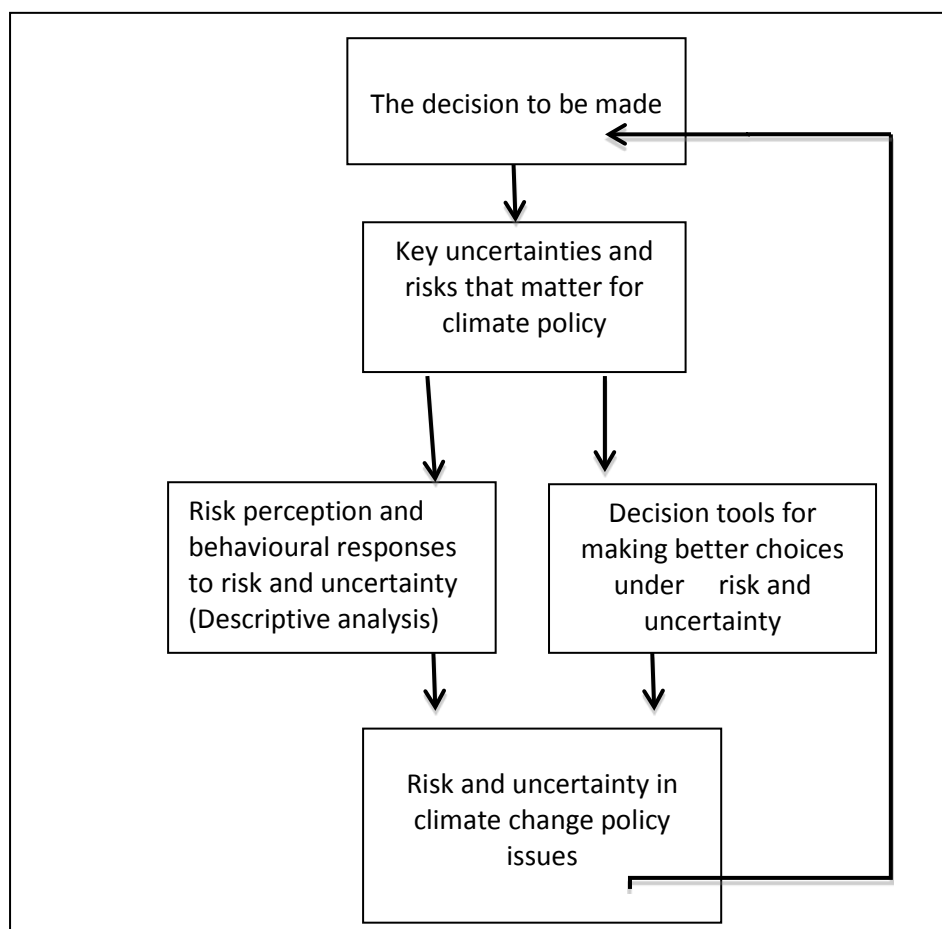
- 18 • A farmer needs to determine how to make use of diversification strategies with respect to
19 planting crops and purchasing insurance to protect against the consequences of drought;
- 20 • A private firm is deciding whether to make investments in solar energy or wind power;
- 21 • A region or community is developing ways for coastal villages in hazard-prone areas to
22 undertake measures for reducing future flood risks that are expected to increase in part due to
23 sea level rise.
- 24 • A government agency is developing a strategy for renewable energy to meet its country's
25 greenhouse gas reduction goals;
- 26 • An NGO is taking steps to assist climate refugees who are migrating due to weather-related
27 factors (e.g., increased heat stress causing crop failure or mass livestock deaths);
- 28 • A national government is developing a position for the next Conference of the Parties (COP) as
29 to what commitments it should make with respect to reducing greenhouse gas emissions;
- 30 • National delegates to the COP are negotiation about the construction of an agreement about
31 mitigation of and adaptation to climate change.
- 32 • To address the issues highlighted by these examples we first define the nature of the risks and
33 uncertainties associated with climate change, how individuals and collective units perceive risk
34 and make decisions in the face of this uncertainty (descriptive analysis) and the tools and
35 approaches that have been employed to improve the choice process (normative analysis). Based
36 on this descriptive and normative analysis we describe the challenges that exist in managing
37 climate change and its impacts through mitigation and adaptation policies in the face of risk and
38 uncertainty.

39 2.1.1 A framework for assessing the role of risk and uncertainty in climate change policy

40 Figure 1 depicts a framework that shows the interconnections between the following elements:

- 41 • The decision to be made
- 42 • Key uncertainties and risks that matter for climate policy
- 43 • Risk perception and behavioural responses to risk and uncertainty

- 1 • Decision tools for making choices under risk and uncertainty
- 2 • Risk and uncertainty in climate change policy issues



3
4 **Figure 2.1** Framework of risk and uncertainty assessment of climate change response policies.

5 We now briefly discuss each of these elements and summarize a set of key points discussed in the
6 other sections of the chapter.

7 **The decision to be made.** One needs to specify a set of alternatives and the accompanying risk and
8 uncertainty in making choices between them. For example, a farmer making decisions on what crops
9 to plant should concern himself with the likelihood and consequences of insufficient rainfall during
10 the next growing season and the uncertainties surrounding such seasonal forecasts. A community
11 determining whether to invest in an irrigation system to deal with the potential consequences of
12 drought has a much longer time horizon to consider and should utilize different climate change
13 scenarios in making this decision. A government implementing a carbon tax needs to be concerned
14 with the uncertainties associated with its ability to monitor firms' activities and the impact of a
15 specific penalty on firms' actions. A national government determining its position on negotiating an
16 international climate agreement on mitigation needs to concern itself with current and future global
17 climate change scenarios and the costs and benefits associated with specific mitigation and
18 adaptation investments. In the sections that follow we will use these and other examples to
19 highlight the elements of the framework depicted in Figure 1.

20 **Key uncertainties and risks that matter for climate policy.** To develop effective and efficient
21 mitigation and adaptation policies, one needs to characterize the nature of the risk and uncertainty
22 associated with policies and decisions that reduce the negative impacts of climate change. The
23 farmer will want to understand the risks and uncertainties of drought in the future and its
24 consequences, given different technologies, programs and policies in place. Communities concerned

1 with developing irrigation systems will want to have an understanding of the drought risk should
2 specific investments be undertaken. Similarly, a government implementing a carbon tax will want to
3 evaluate how its implementation will impact on greenhouse gas (GHG) emissions and the impact of
4 these emissions on the likelihood of different climate change scenarios. Finally, delegates to the
5 Conference of the Parties (COP) will need to understand the benefits, risks and costs of different
6 ways to mitigate climate change and their inherent uncertainties.

7 Section 2.1.1 examines how risk and uncertainty impacts the construction of scenarios and
8 evaluation of policy instruments for mitigating climate change and the climate governance process.
9 The Appendix complements this material by examining the elements of the Guidance Note for Lead
10 Authors of AR5 that specifies how uncertainty with respect to climate change should be reported,
11 treated and communicated.

12 **Risk Perception and behavioural responses to risk and uncertainty.** There is a large literature
13 demonstrating that individuals, small groups and organizations often do not make decisions in the
14 analytic or rational way envisioned by normative models of choice in the economics and
15 management science literature. Risks frequently are perceived in ways that differ from expert
16 judgments. Decision makers tend to be highly myopic and utilize simplified heuristics in choosing
17 between alternatives. To illustrate, farmers may perceive the likelihood of drought to be below their
18 threshold level of concern, even though the risk can be significant, especially over time. A coastal
19 village may decide not to undertake measures for reducing future flood risks due to sea level rise
20 because they focus on the next few years. They conclude that the expected short-term benefits do
21 not justify undertaking protection actions even though the long-term discounted benefits greatly
22 exceed the upfront investment costs of the proposed adaptation measures. Firms may not reduce
23 their emissions if the government imposes a carbon tax because they feel that they will not be
24 forced to pay a penalty because the regulation will not be well enforced. Government instructions to
25 national delegates may be based on the perception that the voting public has a myopic view of
26 climate change.

27 **Section 2.2** provides empirical evidence on behavioural responses to risk and uncertainty by
28 examining the types of biases that influence individuals' perception of the likelihood of an event
29 (e.g., availability, learning from personal experience), the role that emotional, social and cultural
30 factors play in influencing the perception of climate change risks and mental models that individuals
31 utilize in making decisions. The section also addresses the ways people respond to different forms of
32 risk communication and how myopia and impatience impact on actions that individuals take in
33 response to the risk and uncertainties of climate change.

34 **Decision tools for making better choices.** A wide range of tools have been developed for evaluating
35 alternative options and making choices in a systematic manner when probabilities and/or outcomes
36 are uncertain. The appropriate use of these models depends on the nature of the decision and how
37 the key stakeholders deal with uncertain information. Farmers and firms may find the expected
38 utility model or decision analysis as useful tools for evaluating different alternatives under risk and
39 uncertainty when an analyst demonstrates how these models can reduce their costs and/or increase
40 their profits. Communities deciding on whether to invest in irrigation systems that improve the
41 welfare of their farmers may find cost-effectiveness analysis a useful decision aid, while
42 governments debating the merits of a carbon tax may turn to cost-benefit analysis. Integrated
43 assessment models may prove useful to delegates intent on justifying the positions of their
44 governments.

45 **Section 2.3** delineates tools and methodologies for analysing risk and uncertainty when individuals
46 are making choices for themselves and when decision-makers are responsible for actions that affect
47 both themselves and others (i.e. social choices). These tools encompass expected utility theory, the
48 use of integrative assessment models (IAM) in combination with cost-benefit and cost-effectiveness
49 analysis, adaptive management, robust decision making and uncertainty analysis techniques such as

1 structured expert judgment and scenario analysis. The chapter highlights the importance of selecting
2 different methodologies for addressing different problems.

3 **Risk and uncertainty in climate change policy issues.** Policies should take into account risk
4 perception and behavioural responses to information and data while at the same time utilizing the
5 tools and methodologies for improving decisions related to uncertainty and risk. Section 2.4
6 examines how the outcomes of particular options, in terms of their efficiency or equity, are sensitive
7 to risks and uncertainties. We start with decisions at the broadest possible geographical and
8 temporal scales, namely the selection of long-term global greenhouse gas emissions and
9 concentration targets and stabilization pathways for dealing with uncertainty from the social
10 planner's perspective and the structuring of international negotiations and paths to reach
11 agreement. The section also examines strategies for gaining public support for adaptation and
12 mitigation policies at various levels of governance as well as making the adoption of technologies
13 more attractive economically under conditions of risk and uncertainty. These include pathways to
14 achieve pre-selected targets, the specific instruments and interventions designed to do so, and the
15 effects of risk and uncertainty on private sector investments of many kinds.

16 The way climate change is managed will impact on the actual decision to be made as shown by the
17 feedback loop in Figure 1. This feedback loop can be illustrated by the following examples.
18 Individuals may be willing to invest in solar panels if they are able to spread the upfront cost over
19 time through a long-term loan. Firms may be willing to promote new energy technologies that
20 provide social benefits with respect to climate change if they are given a grant to assist them in their
21 efforts. National governments are more likely to implement carbon markets or international treaties
22 if they perceive the short-term benefits of these measures to be greater than the perceived costs.

23 2.1.2 Key uncertainties and risks that matter for climate policy

24 Policies are strategies for satisfying a set of specific objectives or criteria. In this chapter, we
25 consider the ways in which risk and uncertainty can affect the process and outcome of strategic
26 choices to respond to the threat of climate change. These choices are likely to involve international
27 targets for greenhouse gas emissions reduction or adaptation, national and regional governmental
28 interventions, and private sector decisions to invest in new infrastructure or technologies. The risks
29 and uncertainties themselves can stem from numerous sources such as a lack of understanding
30 about how a system or process operates, imprecise data on previous system states from which to
31 parameterize forecasting models, or an inability to predict how other decision-makers, organizations
32 or countries will behave. In systems that are complex—having multiple interactions between the
33 different elements—small differences in initial conditions may result in larger differences over time,
34 making it impossible to predict exactly how the system will develop. In many cases, scientific
35 research and investments in data gathering can reduce uncertainty. Sometimes, research uncovers
36 the importance of uncertainties that scientists had not previously considered, making outcomes
37 even more difficult to predict than they had been previously.

38 The presence of risk and uncertainty can affect the process by which actors make such decisions:
39 how much time, effort and computation they devote to examining specific problems they face. Do
40 they focus their analysis on the most likely outcomes that from their choices or those that are
41 unlikely to occur but if they do will result in severe consequences. Do they employ systematic
42 algorithms for aiding their decisions-making process or rely on their intuition and experience-guided
43 judgment? Do they plan ahead with the intent of possibly change their decisions in the future when
44 they reexamine the uncertainties associated with the likelihood and consequences of specific
45 outcomes.

46 The presence of risk and uncertainties can also influence the outcomes of specific choices. Some
47 government interventions, for example, directly address the risks and uncertainties inherent in a
48 system by spreading risk across a wider pool of actors or by minimizing volatility in markets. Some
49 investments in infrastructure or technologies may not make sense from the perspective of their

1 expected costs and benefits, but can be justified if they protect the investor from experiencing very
2 large losses. Careful consideration of the relevant uncertainties could potentially shift decisions
3 towards such interventions and investments.

4 The uncertainties that matter for policy choices are associated with a number of different variables.
5 Here we classify the uncertainties and risks into five distinct areas:

- 6 • *Climate impacts and damage costs.* The large number of key uncertainties with respect to the
7 climate system are discussed by Working Group I. These uncertainties in the climate system
8 cascade into even greater uncertainties with respect to climate impacts. The costs of those
9 impacts on society are examined in Working Group II. The idea that the climate system has “fat
10 tails,” or that the right-hand tail the distribution of climate never diminishes to zero, has
11 suggested that greenhouse gas emissions reduction targets need to focus on the potential
12 catastrophic consequences of low-probability high-impact events (Weitzman, 2009a). Another
13 area of concern is the possibility of tipping points, defined by (Walker, 2006) as the moment at
14 which internal dynamics propels a change previously driven by external forces. This possibility
15 should also guide the targets for greenhouse gas emissions and adapting to a wider possible
16 range of possible climate impacts than may not have been previously considered.
- 17 • *Technologies and technological systems.* Technology deployment is often a critical aspect of both
18 adaptation and mitigation policies. In the adaptation area infrastructure technologies such as
19 levees and flood-walls can protect residents from climate impacts due to sea level rise. Irrigation
20 systems can protect farmers against the consequences of drought on their crop yields. In the
21 mitigation area technologies for energy transmission, storage, and greater energy efficiency can
22 reduce carbon emissions. Many of these technologies are new or in stages of rapid
23 improvement. It is thus unclear how they will perform, how expensive they will be, and what
24 environmental, health, or safety risks they might present. The technologies that governments
25 will support, private sector firms and entrepreneurs will invest in and the general public will
26 embrace are likely to be sensitive to these uncertainties.
- 27 • *Future development pathways.* The state of the environment and society in the future are likely
28 to be determined in large part by factors other than climate change. The previous two
29 assessment reports have characterized a possible set of development pathways using SRES
30 scenarios differing in their relative attention to economic growth or sustainable development on
31 the one hand, and global integration or fragmentation on the other (Nakicenovic and Swart,
32 2000). These divergent storylines enabled one to develop a set of baseline emissions pathways
33 as inputs for climate models. The baselines also permitted the evaluation of alternative
34 internally consistent future socio-economic conditions that would influence the cost of climate
35 mitigation (Knopf et al., 2010), or people’s adaptive capacity and climate vulnerability (Patt et
36 al., 2010). A new set of shared socio-economic pathways (SSPs) has been developed for this
37 assessment report. They highlight differences in possible future greenhouse gas emissions, the
38 costs and benefits of emissions reductions, and people’s vulnerability to impacts.
- 39 • *Future regulations and their effects.* Climate policy for adaptation and especially mitigation is
40 concerned with creating incentives for the private sector actors to alter their investment
41 behaviour. Many incentive instruments—such as taxes, carbon markets, subsidies, or technology
42 quotas—are relatively new policy developments, and their effectiveness is still being tested and
43 evaluated. As Knopf and Edenhofer (2010) report, energy models based on a Ramsey (1926)
44 growth model of the economy predict net reductions in global economic activity as a result of
45 market-based policy interventions to achieve a 2°C target. On the other hand, a Keynesian
46 model of the economy predicts net increases in global economic activity as a result of the same
47 set of interventions. Policy makers’ choices about which interventions to favour is likely to be
48 sensitive to such uncertainties. Investment choices of private actor will also be influenced by
49 these uncertainties and further compounded by the uncertainty as to what future climate policy

1 will be. This so-called *regulatory uncertainty* has led to a number of studies as to how private
2 actors behave, and hedge their bets, when they do not know how future policies will affect the
3 economic rewards to alternative investment choices.

- 4 • *Preferences and perceptions.* In making climate change policy decisions it is important to
5 understand and be able to predict how people behave today and are likely to react to future
6 conditions. The anticipated costs of climate change in the future depends on how our children
7 and grandchildren adapt to the environment in which they are living and the new configuration
8 of ecosystem services. The outcome of international climate negotiations depend on how
9 individual negotiators perceive the preferences of the parties across the table and the
10 techniques they utilize to motivate them to undertake specific actions. Government policies to
11 incentivize particular investments in new technology or infrastructure also depend on
12 assumptions regarding the perceptions and preferences of key decision makers and the factors
13 driving their choices between alternatives including maintaining the status quo.

14 Most of these areas of risk and uncertainty have to do with the behavior of people and of social
15 systems, and relatively less to do with the behavior of natural systems, such as the climate or of
16 ecosystem response. To date, there has been some research focused on the effects of natural
17 system uncertainty on climate policy, and relatively little examining the impact of risk and
18 uncertainty on social systems. This can partially be explained by the fact that one crucial policy
19 decision—setting global emissions reductions targets—is particularly sensitive to natural system
20 uncertainty. As policy moves forward, uncertainties in social systems are likely to become more
21 important, as discussed in Section 2.4.

22 2.1.3 Storyline for this chapter

23 The key points of the chapter can be summarized as follows:

- 24 • There is an evolving set of choices and decisions related to climate policy that are being made
25 and need to be made given the risks and uncertainties associated with the natural system and
26 their impact on social systems.
- 27 • In choosing between alternatives and making decisions the relevant interested parties often
28 misperceive the risks and use simplified decision rules (**Sect. 2.2**)
- 29 • Some decision tools can aid these interested parties in improving their choices for a set of
30 climate-related problems. (**Sect. 2.3**)
- 31 • In designing mitigation and adaptation measures for reducing the impacts of climate change one
32 needs to take into account how risk and uncertainty influences the effectiveness of different
33 policy instruments, options the private and public sectors might promote for managing
34 technological change and processes by which key decision makers design and implement climate
35 policy. (**Sect. 2.4**)

36 2.2 Perceptions and behavioral responses to risk and uncertainty

37 A key challenge in designing mitigation and adaptation measures to reduce climate change risks is to
38 recognize the limitations of decision makers in dealing with risk and uncertainty and to design tools
39 that help them make more informed choices. Daniel Kahneman in his book *Thinking, Fast and Slow*
40 (2011) captures decades of behavioural decision research by characterizing two modes of thinking,
41 called System 1 and System 2:

- 42 • System 1 operates automatically and quickly with little or no effort and no sense of voluntary
43 control and uses simple associations, including emotional reactions, that have been acquired by
44 personal experience with events and their consequences.

- 1 • System 2 initiates and executes effortful and intentional mental activities as needed, including
2 simple or complex computations or formal logic.
- 3 Even though the operations of these two processing systems do not map cleanly onto distinct brain
4 regions and the two systems often operate cooperatively and in parallel (Weber and Johnson, 2009;
5 Kahneman, 2011) argues convincingly that the distinction between System 1 and 2 helps to make
6 clear the tension between automatic and largely involuntary processes and effortful and more
7 deliberate processes in the human mind.
- 8 Many of the biases and simplified decision rules that characterize human judgment and choice under
9 uncertainty described in this section reflect the more automatic and less analytic System 1. They are
10 not only found among the general public but reflect choices by technical experts and policy makers,
11 and decisions made by groups and firms (Cyert and March, 1963; Cohen et al., 1972) . When the
12 calibration of probability judgments of experts has been examined, only those who receive frequent
13 and timely feedback on the accuracy of their assessments, namely weather forecasters (Murphy and
14 Winkler, 1984) and professional bridge players (Keren, 1987) have been found to perform well.
15 Expert risk assessors in toxicology, while still exhibiting some systematic biases in their risk
16 judgments, have shown greater sensitivity in their judgments of the risks associated with exposure
17 to chemicals than members of the public (Kraus et al., 1992). Their behavior suggests that there is a
18 continuum with respect to the use by decision makers of their natural System 1 responses to risk
19 and uncertainty and their resorting to more formal System 2 methods. In cases where the outputs
20 from the two processing systems disagree, the affective, association-based System 1 usually prevails,
21 because its output comes in faster and is more vivid, and thus more likely to capture a person's
22 attention, dominating the often far more reliable and diagnostic statistical information (Erev and
23 Barron, 2005).
- 24 The decision tools and models described in Section 2.3 require the decision maker to utilize System 2
25 and make deliberative choices in a systematic manner. In various parts of the chapter we will
26 highlight the role that each of these two systems play in influencing choices by individuals, firms,
27 countries and multinational groups. Whereas the social planner can be expected to utilize System 2
28 processes to a greater degree than individual decision makers, System 1 and 2 processes influence
29 judgments and choices at all levels.
- 30 A key feature of behaviour under System 1 is a tendency to focus on the short run and be myopic
31 when thinking about possible responses to climate change risks and their associated uncertainties.
32 System 2 analyses recognize the need to develop long-term strategies for dealing with the
33 consequences of climate change over the next 50 to 100 years. However, implementing these
34 proposed solutions may be difficult in the face of System 1 perceptions and reactions to climate
35 risks. **Section 2.5** suggests future research needs for designing long-term policies that have a chance
36 of being implemented today by recognizing and counteracting the human tendency to be myopic.
- 37 In this section we focus on perceptions of and reactions to the uncertainties and risks of climate
38 change. Empirical evidence from social science research reveals that perceptions and responses
39 depend not only on objective reality but also on the observers' internal states, needs, and cognitive
40 and emotional processes. Individuals' perceptions and responses to risk and uncertainty are
41 malleable and labile, such as being subject to variations in the situational context. It matters how
42 information about the risk is acquired and presented, factors that do not play a role in normative
43 models of choice such as expected utility theory (Lichtenstein and Slovic, 2006; Weber and Johnson,
44 2009).
- 45 This System 1 behavior is particularly relevant for low probability-high consequence risks such as
46 increased flooding and storm surge possibly due to sea level rise. For such climate risks, there is
47 limited personal experience and historical data and considerable disagreement and second-order
48 uncertainty among experts in their risk assessments. System 2 responses to such uncertainty with

1 potentially catastrophic consequences may invoke the use of the precautionary principle, robust
2 decision-making or other heuristics discussed in **Section 2.3**.

3 **2.2.1 Risk perception of uncertain events**

4 Evidence from cognitive, social, and clinical psychology indicates that the perception of risk is
5 influenced by System 1 associative processes (i.e., connections between objects or events
6 contiguous in space or time, resembling each other, or having some causal connection (Hume, 2000;
7 Weber, 2006) and affective processes (i.e., processes influenced by emotions) as much or more than
8 by analytic processes. (see Weber, 2006). Perceptions of the risks associated with a given event or
9 hazard are strongly influenced by personal experience and therefore can differ between individuals
10 as a function of their location, history, and/or socio-economic circumstances, (Figner and Weber,
11 2011).

12 There are two psychological risk dimensions that influence people's intuitive perceptions of health
13 and safety risks in ways common across numerous studies in multiple countries. (Slovic, 1987). The
14 first factor, dread risk, captures emotional reactions to hazards like nuclear reactor accidents, or
15 nerve gas accidents, i.e., things that make people anxious because of a perceived lack of control over
16 exposure to the risks and because consequences may be catastrophic. The second factor, unknown
17 risk, refers to the degree to which a risk (e.g., DNA technology) is perceived as new, with
18 unforeseeable consequences and with exposures not easily detectable. The human processing
19 system maps both the uncertainty and the adversity components of risk into affective responses and
20 represents risk as a feeling rather than as a statistic (Loewenstein et al., 2001). These associative
21 and affective processes are automatic and fast and are available to everyone from an early age, as is
22 typical of System 1 thinking. Analytic assessments of risk such as probability estimation, Bayesian
23 updating, and formal logic, must be taught and require conscious effort as is typical of System 2
24 thinking. Psychological research over the past decade has documented the prevalence of affective
25 processes in the intuitive assessment of risk, depicting them as essentially effort-free inputs that
26 orient and motivate adaptive behaviour, especially under conditions of uncertainty (Finucane et al.,
27 2000; Loewenstein et al., 2001; Peters et al., 2006).

28 Leiserowitz (2006) applied a methodology developed by (Slovic et al., 1991) to assess the emotional
29 valence of people's reactions to the risk of climate change. He asked people in the U.S. to provide
30 the first thought or image that came to mind when hearing the term global warming. Their
31 responses were then rated on a scale ranging from -5 (very negative) to +5 (very positive).
32 Associations like melting glaciers and polar ice were most common, followed by generic associations
33 to heat and rising temperatures. Mean scores indicated that these images had only moderately
34 negative connotations.

35 Personal experience affects risk perceptions often by way of people's affective reactions (Keller et
36 al., 2006). Whereas personal exposure to adverse consequences increases fear and perceptions of
37 risk, familiarity with a risk without adverse consequences can lower perceptions of its riskiness
38 (Fischhoff et al., 1978). This suggests that greater familiarity with climate risks, unless accompanied
39 by alarming negative consequences, could actually lead to a reduction rather than an increase in the
40 perceptions of its riskiness. Seeing climate change as a simple and gradual change from current to
41 future values on variables such as average temperatures and precipitation may make it seem
42 controllable, e.g., by moving to a different part of the country and less dreaded than rapid climate
43 change (Weber, 2006). These psychological dimensions of risk perception challenge the rational-
44 economic and engineering and policy conceptualization of risk as something objective (Slovic, 1999).

45 **2.2.1.1 Learning from personal experience vs. statistical description**

46 Recently, a distinction has been made between learning about uncertain events or environments
47 from personal experience and by being provided with numeric or graphic summary descriptions of
48 possible outcomes and their likelihoods. Learning about uncertain events, be they adverse weather

1 events or possible outcomes of different climate risk mitigation or adaptation responses, from
2 repeated personal experience capitalizes on the automatic, effortless, and fast associative and
3 affective processes of System 1 (Weber et al., 2004). Learning from statistical descriptions, on the
4 other hand, requires System 2 processes (e.g., understanding numerical probabilities and probability
5 theory) that need to be learned and require cognitive effort.

6 Judging the likelihood of extreme climate events or climate change consequences on any given day
7 from personal experience may suggest that it is highly unlikely if the individuals have limited
8 exposure to the event so they do not become alarmed even if their economic livelihood depends on
9 weather and climate events (e.g., farmers or fishers). Surveys conducted in Alaska and Florida,
10 where residents in some regions have been exposed more regularly to physical evidence of climate
11 change, show that such personal exposure greatly increases their concern and willingness to take
12 action (Assessment, 2004; Leiserowitz and Broad, 2008; Mozumder et al., 2011).

13 Most people consider themselves experts on the weather and do not differentiate between climate,
14 climate variability and weather (Bostrom et al., 1994; Cullen, 2010). People's expectations of change
15 (or stability) are important in their ability to detect trends in probabilistic environments, as
16 illustrated by the following historic climate example Kupperman (1982) reported in Weber (1997)
17 and Stern and Easterling (1999). English settlers who arrived in North America in the early colonial
18 period assumed that climate was a function of latitude. Newfoundland, which is south of London,
19 was thus expected to have a moderate climate. Despite repeated experiences of far colder
20 temperatures and resulting deaths and crop failures, colonists clung to their expectations based on
21 latitude, and generated ever more complex explanations for these deviations from expectations.

22 In a more recent example, farmers in Illinois were asked to recall salient growing season
23 temperature or precipitation statistics for seven preceding years (Weber, 1997). Farmers who
24 believed that their region was undergoing climate change recalled temperature and precipitation
25 trends consistent with this expectation, whereas farmers who believed in a constant climate,
26 recalled temperatures and precipitations consistent with that belief. Recognizing that expectations
27 and beliefs shape perception and memory, provides insight into the variation in the expectations of
28 climate change vs. climate stability between segments of the U.S. population groups that differ on
29 political ideology.(Leiserowitz et al., 2008).

30 A recent study of a representative sample of the in Britain public assessed perceptions and beliefs
31 about climate change and behavioural intentions to reduce personal energy use to reduce
32 greenhouse gas emission. About 20 percent of the individuals had experienced recent flooding in
33 their local area, while others had not (Spence et al., 2011). Concern about climate change was
34 greater in the group of residents who had experienced recent flooding. Even though the flooding
35 was only a single and local data point, this group also reported less uncertainty about whether
36 climate change was really happening than those who did not experience flooding recently. This view
37 would be influenced by media coverage and increasing scientific evidence of a link between changes
38 in average global temperatures and the likelihood of severe rainstorms that have given rise to
39 flooding events observed in the UK with increasing frequency and severity over the past decade.

40 **2.2.1.2 Availability**

41 People often assess the likelihood of an uncertain event by the ease with which instances of its
42 occurrence can be brought to mind, a form of behaviour characterized as availability by (Tversky and
43 Kahneman, 1973) and impacted by personal experience. Availability can lead to an underestimation
44 of low probability events such as extreme weather (frosts, flooding, or droughts) before they occur
45 and an overestimation after a disaster. The availability bias can explain the interest in individuals
46 purchasing insurance after a disaster occurs and cancelling their policies several years later as
47 revealed by data with respect to the demand for earthquake and flood insurance. (Kunreuther et al.,
48 1978; Michel-Kerjan et al., 2012) as discussed in Section 2.2.4.

1 People confound climate and weather in part because they have personal experience with weather
2 and weather abnormalities but little experience with climate, and thus substitute weather events for
3 climate events. Judging climate change from personal experience of local weather abnormalities can
4 easily distort risk judgments (Li et al., 2011). The use of availability as a heuristic and its connection
5 to differences among groups, cultures, and nations in responses to climate change risks is discussed
6 by (Sunstein, 2006).

7 Public perceptions of climate change over time (as reflected by opinion polls, e.g., Pew Research
8 Center, 2006, 2009) seem to reflect a general under-concern and greater volatility than warranted
9 by scientific evidence, a finding consistent with earlier research (Yechiam et al., 2005). The Pew
10 Research Center (2009) poll found that while 84% of scientists said the earth was getting warmer
11 because of human activity such as burning fossil fuels, only 49% of non-scientists in this U.S.
12 representative sample held this view. Weber and Stern (2011) summarize physical, psychological,
13 and social factors that explain why public understanding in the United States has not tracked
14 scientific understanding. The few studies that have assessed climate change risk perceptions in
15 developing countries find similar results though generally higher levels of concern about climate
16 change, reflecting greater perceptions of vulnerability (Vignola et al., 2012).

17 **2.2.1.3 Other factors influencing perceptions of climate change risks**

18 Climate change is a complicated phenomenon with a few climate drivers causing multiple hazards
19 (Kempton, 1991; Bostrom et al., 1994; NRC, 2010). Mental models of causal connections between
20 concepts or variables help people with finite processing capacity comprehend complex phenomena.
21 Non-scientists' mental models about climate change have been shown to diverge from those of
22 climate scientists (Kempton, 1991; Bostrom et al., 1994). When climate change first emerged as a
23 policy issue, people often confused it with the loss of stratospheric ozone resulting from releases of
24 chlorofluorocarbon. As the "ozone hole" issue has receded from public attention, this confusion has
25 become less prevalent (Reynolds et al., 2010). Instead, greenhouse gases are often wrongly equated
26 with more familiar forms of pollution, with the incorrect inference that "the air will clear" soon after
27 emissions are reduced (Sterman and Sweeney, 2007), even though most greenhouse gases continue
28 to warm the planet for decades or centuries after they are emitted (Solomon et al., 2009).

29 There are also motivational challenges to a rational processing of climate risks and existing
30 uncertainty about climate change, its physical and social consequences, and potential responses.
31 There is large systemic uncertainty as well as expert disagreement about many forecasts, and the
32 pool of technologically and politically possible solutions is extremely small, giving rise to feelings that
33 things might be or become uncontrollable. Given that the feeling of being in control is an important
34 human need (Langer, 1975) and that people are anxious to avoid negative mood states, there are
35 emotional incentives to minimize or deny climate risks (Swim et al., 2010).

36 Mitigation or adaptation responses that provide solutions to existing or future climate risks require
37 tradeoffs with individual and social goals, such as continued use of familiar and reliable energy
38 sources and economic growth and development. People's reluctance to acknowledge the need for
39 tradeoffs has been documented in situations far less consequential than climate change and has
40 given rise to simplifying decision rules such as lexicographic models that eliminate choice options
41 (Payne et al., 1988).

42 The cognitive demand of a calculated response to climate risks normally loses out to behavior that
43 satisfies emotional needs and minimizes tradeoffs. Motivated cognition is the label for a tendency to
44 bias interpretation of facts to fit a version of the world we wish to be true. Motivated reasoning, as
45 exhibited by the confirmation bias (i.e., a tendency to attend to evidence confirming favored beliefs)
46 tends to steer individuals to System 1 behavior. More specifically, wishful thinking and motivated
47 cognition in the face of growing evidence of climate risks helps explain increased polarization in
48 attitudes and beliefs about climate change over the past two decades rather than a System 2

1 process where one examines data in a careful manner and undertakes tradeoffs in making choices
2 between alternative courses of action.

3 **2.2.2 Risk communication challenges**

4 Climate scientists face many types of uncertainties in making forecasts with respect to the future
5 that if not communicated accurately, may lead others to misperceptions of the corresponding
6 climate risks by the general public (Corner and Hahn, 2009). Krosnick et al. (2006) found that
7 perceptions of the seriousness of global warming as a national issue were predicted by (1) the
8 degree of certainty that global warming is occurring and will have negative consequences and (2)
9 whether there is a recognition that humans are causing the problem and have the ability to solve it.
10 Accurately communicating uncertain climate risks are therefore a critically important challenge for
11 climate scientists and policymakers (Pidgeon and Fischhoff, 2011).

12 People respond to uncertainty in qualitatively different ways depending on whether the possible
13 outcomes are perceived as favorable or adverse (Smithson, 2008). The significant time lags within
14 the climate system lead many people to incorrectly believe global warming will have only
15 moderately negative impacts. For example, despite the fact that “climate change currently
16 contributes to the global burden of disease and premature deaths” (IPCC, 2007) relatively few
17 people make the connection between climate change and human health risks (Akerlof et al., 2010).

18 People also prefer concrete representations of uncertainty that relate to their personal and local
19 experience (Marx et al., 2007). Global warming has already led to changes in the frequency and
20 severity of heat waves and heavy precipitation events in many parts of the world (IPCC, 2012)
21 leading a large majority of Americans to think that it has made several high profile extreme weather
22 events worse (Leiserowitz et al., 2012). That said, the perception that the impact of climate change is
23 neither immediate nor local persists (Leiserowitz et al., 2008) leading many to think it rational to
24 advocate a “wait-and-see” approach to emissions reductions (Leiserowitz, 2007; Sterman, 2008).

25 Individual and group differences in cognitive abilities and the use of different cognitive and affective
26 processes have additional implications for risk communication (Budescu et al., 2009). Numeracy, the
27 ability to reason with numbers and other mathematical concepts, is a particularly important
28 construct in this context (Peters et al., 2006) as it has implications for the presentation of likelihood
29 information using either numbers (e.g., 90%) or words (e.g., “very likely” or “likely”) as well as
30 different pictorial forms (e.g., graphs, box plots, diagrams). A further discussion of how to
31 communicate scientific findings and their accompanying uncertainties appears in the Appendix. To
32 satisfy people’s preference for concrete rather than statistical representations, scientists (including
33 those on the IPCC) have started to translate probabilistic forecasts into a small set of scenarios (e.g.,
34 best-to-worst case). Such scenario representation has been shown to facilitate strategic planning by
35 professional groups such as military commanders, oil company managers, and policy makers in other
36 contexts (Schoemaker, 1995).

37 These behavioral and cognitive science insights highlight some of the challenges facing scientists and
38 policymakers in their efforts to develop effective climate change risk communication strategies and
39 raise important questions about whether efforts to guide System 1 learning might be used to
40 stimulate System 2 behavior.

41 **2.2.2.1 Social amplification of risk**

42 Hazards interact with psychological, social, institutional, and cultural processes in ways that may
43 amplify or attenuate public responses to the risk or risk event. Amplification may occur in the
44 transfer of information about the risk by scientists, news media, cultural groups, interpersonal
45 networks, and others. The amplified risk leads to behavioral responses, which, in turn, may result in
46 secondary impacts (Kasperson et al., 1988).

47 Leiserowitz (2004) explored the impact of the social amplification of risk by conducting a study on
48 the impact of the film *The Day After Tomorrow* on attitudes toward climate change in the United

1 States. The film led moviegoers to have higher levels of concern and worry about global warming,
2 and encouraged watchers to engage in personal, political, and social action to address climate
3 change. He also noted that it did not change general public opinion because of the limited number of
4 individuals who watched the movie. Since the survey was conducted shortly after the film was
5 released it could not determine how long-lasting this increased concern with climate change would
6 be.

7 **2.2.3 Factors influencing responses to risk and uncertainty**

8 This section introduces phenomena in people's decisions or non-decisions under risk and uncertainty
9 that are typically the result of System 1 processes. The extent to which individuals exhibit each
10 choice pattern is captured in descriptive models of choice under uncertainty (Tversky and
11 Kahneman, 1992) and delayed consequences (Laibson, 1997) by a model parameter. Adaptive
12 testing methods that utilize Bayesian estimation procedures enable one to assess individual
13 differences in these model parameters (Toubia et al., 2012).

14 *Loss aversion.* Loss aversion is an important property that distinguishes prospect theory (Tversky and
15 Kahneman, 1992) from expected utility theory (von Neumann and Morgenstern, 1944). Prospect
16 theory introduces a reference-dependent valuation of outcomes, with a steeper slope for perceived
17 losses than for perceived gains. In other words, there is a greater disutility for outcomes that are
18 encoded as losses than there is utility for outcomes of the same magnitude that are encoded as
19 gains relative to a given reference point. Loss aversion explains a broad range of laboratory and real
20 world choices that deviate from the predictions of expected utility theory (Camerer, 2000). Letson et
21 al. (2009) show that land allocation to crops in the Argentine Pampas, as an adaptation to existing
22 seasonal-to-interannual climate variability depends not only on objective economic circumstances
23 (e.g., whether the farmer is renting the land or owns it,), but also on individual differences in the
24 farmer's behavior. For example, if a farmer is attempting to maximize his returns by utilizing an
25 expected utility model he will likely choose a different crop allocation pattern than if he made his
26 decision utilizing prospect theory by focusing on a reference point such as past returns. The crop
27 allocation decision will also be influenced by degree of risk aversion and the magnitude of loss
28 aversion.

29 **Status quo bias.** There is a tendency for individuals to maintain their current behaviour if their
30 reference point for making decisions is the status quo. Given loss aversion, the negative
31 consequences from moving away from the status quo are weighted much more heavily than the
32 potential gains, often leading the decision maker not to take action (Samuelson and Zeckhauser,
33 1988).

34 **Quasi-hyperbolic time discounting.** Normative models suggest that future costs and benefits should
35 be evaluated using an exponential discount function where the discount rate reflects the decision-
36 maker's opportunity cost of money. In reality, people discount future costs or benefits much more
37 sharply. (Loewenstein and Elster, 1992). Laibson (1997) characterized the process by a quasi-
38 hyperbolic discount function, with two discounting parameters β (present bias) and δ (rational
39 discounting), each taking values between 0 and 1. The "beta-delta" model retains much of the
40 analytical tractability of exponential discounting while capturing the key qualitative feature of
41 discounting with true hyperbolas. One explanation for this behavior is that future events (e.g. the
42 prospect of coastal flooding 5 or 20 years from now) are construed abstractly, whereas events closer
43 in time (the prospect of a major hurricane passing through town tomorrow) are construed more
44 concretely (Trope and Liberman, 2003). The abstract representations of consequences in the distant
45 future do not generate the emotional reactions of present or near-present events and hence do not
46 elicit similar concerns nor action. Many effective and efficient climate change responses like
47 investments into household energy efficiency are not adopted because of decision makers' excessive
48 discounting of future consequences.

1 **Non-linear decision weights.** The probability weighting function of prospect theory (Kahneman and
2 Tversky, 1979; Tversky and Kahneman, 1992) captures the nonlinearity by which objective
3 probabilities get translated into decision weights. Low probabilities tend to be overweighted relative
4 to their objective probability unless they are perceived as being so low that they are ignored because
5 they are below the decision-maker's threshold level of concern. (See Section 2.2.4.4.)

6 **Ambiguity aversion.** The Ellsberg paradox (Ellsberg, 1961) revealed that, in addition to being risk
7 averse, most decision makers are also ambiguity averse, i.e., prefer well-specified probabilities
8 (e.g., .5; risk) to ambiguous probabilities. Heath and Tversky (1991) demonstrated, however, that
9 ambiguity aversion is not present when decision makers believe they have expertise in the domain
10 of choice. In contrast to the many laypersons who consider themselves to experts in sports or the
11 stock market, relatively few believe themselves to be highly competent in environmentally-relevant
12 technical domains such as the tradeoffs between hybrid electric vs. conventional gasoline engines in
13 cars so they are likely to be ambiguity averse.

14 **2.2.4 Behavioral responses to risk and uncertainty of climate change**

15 We now turn to how the processes introduced in the previous section influence behavioural
16 responses to the risk and uncertainty of climate change.

17 **2.2.4.1 Cognitive myopia and selective attention**

18 People's unguided analytic consideration of the costs and benefits of different responses to low
19 probability climate change or climate impact events has its own set of problems that include
20 cognitive myopia (i.e., focus primarily on short-term consequences) and selective attention. In the
21 area of adaptation and the management of climate-related natural hazards such as flooding, an
22 extensive empirical literature shows low adoption rates by the general public due to System 1
23 behavioural factors such as myopia and misperception of the risk due to the availability bias. Thus
24 few people living in flood prone areas purchase subsidized flood insurance, even when it is offered
25 at highly subsidized premiums even though System 2 decision tools that could be applied to the
26 problem would have recommended buying this insurance. (Kunreuther et al 1978). Analysis of the
27 National Flood Insurance Program data base from 2001-2009 reveals that many homeowners who
28 have purchased flood insurance cancel their policies several years later, because no flood has
29 occurred. It is difficult to convince them that the best return on an insurance policy is no return at all
30 (Michel-Kerjan et al., (2012))

31 In the context of climate change response decisions, energy efficient refrigerators command a higher
32 price than standard refrigerators, which is viewed as an extra upfront cost. The energy savings from
33 the more expensive refrigerator are delayed in time and somewhat uncertain, and their strong
34 discounting introduces a bias towards environmentally less responsible choices.

35 At a country or community level, the upfront costs of mitigating CO2 emissions or of building
36 seawalls to reduce the effects of sea level rises similarly loom large due to loss aversion, while the
37 uncertain and future benefits of such actions are more heavily discounted than would be implied if
38 one used an exponential function as implied by normative models. Such accounting of present and
39 future costs and benefits on the part of consumers and policy makers makes it difficult for them to
40 justify these investments today and arrive at socially-responsible and long-term sustainable
41 decisions.

42 **2.2.4.2 Myopic focus on short-term goals and plans**

43 Krantz and Kunreuther (2007) emphasize the importance of goals and plans as a basis for making
44 decisions. In the context of climate change, protective or mitigating actions often require sacrificing
45 short-term goals that are highly weighted in people's choices to meet more abstract, distant goals
46 that are typically given very low weight. A strong focus on short-term goals (e.g., immediate survival)
47 may have been adaptive in evolutionary times, but has less importance in the current environment
48 of complex problems with solutions that require long time horizons. Weber et al. (2007) succeeded

1 in drastically reducing people's discounting of future rewards by prompting them to first generate
2 arguments for deferring consumption, contrary to their natural inclination to first consider
3 arguments for immediate consumption. A generally helpful tool to deal with uncertainty about
4 future objective circumstances as well as subjective evaluations is the adoption of multiple points of
5 view (Jones and Preston, 2011) or multiple frames of reference (De Boer et al., 2010), a
6 generalization of the IPCC's scenario approach to an uncertain climate future.

7 **2.2.4.3 Changing reference points and default options**

8 Choice architecture characterizes the process of changing the options and the context of a decision
9 to overcome the pitfalls of System 1 processes without requiring decision makers to switch to
10 effortful System 2 processing (Thaler and Sunstein, 2008). Prospect theory (Tversky and Kahneman,
11 1992) provides policy makers with such a choice architecture design tool, namely the ability to
12 change decision makers' reference points and hence the way outcomes get evaluated. The purchase
13 of an insurance policy against drought by a farmer, for example, involves a sure out-of-pocket loss of
14 money (the insurance premium) for the unsure and low-probability benefit of avoiding a much larger
15 loss in the case of drought. Prospect theory predicts risk-seeking in the domain of losses, which
16 would mean choosing the probabilistic loss over the sure loss. By moving the farmer's reference
17 point away from the status quo--its usual position-- to a possible large loss due to the occurrence of
18 a drought, smaller losses (including the insurance premium) are now to the right of this new
19 reference point in the domain of (foregone) gains. In this region, decision-makers are generally risk-
20 averse and will thus choose the sure option of buying the insurance rather than risk experiencing a
21 severe loss from a future drought.

22 Another choice architecture tool comes in the form of behavioural defaults, i.e., recommended
23 options that will obtain if no active decision is made to change from this pre-specified choice (Weber
24 and Johnson, 2009). Defaults work because they are viewed as a reference point so that decision
25 makers decide not to change from it due to loss aversion. (Weber et al., 2007); (Johnson et al.,
26 2007). Green defaults have been found to be very effective in lab studies involving choices between
27 different lighting technology (Dinner et al., 2011), suggesting that environmental friendly and cost-
28 effective energy efficient technology will find greater deployment if it shows up as the default option
29 in building codes and other regulatory contexts. Green defaults are desirable policy options because
30 they guide decision makers towards individual and social welfare maximizing options without
31 reducing choice autonomy. In a field study, German utility customers adopted green energy defaults
32 that persisted over time (Pichert and Katsikopoulos, 2008).

33 **2.2.4.4 Threshold models of choice**

34 Consistent with their desire not to make tradeoffs when choosing between alternatives, prior to a
35 disaster people often perceive the likelihood of catastrophic events occurring as below their
36 threshold level of concern. Hence they do not consider resulting consequences of a catastrophic
37 event occurring (Camerer and Kunreuther, 1989). The need to take steps today to deal with the
38 consequences of climate change presents a particular challenge to individuals who are myopic and
39 utilize quasi-hyperbolic discount rates. There have a tendency to ignore long-term warnings by using
40 a threshold model and not take action now. The problem is compounded by the inability of
41 individuals to distinguish between likelihoods that differ by one or even two orders of magnitude of
42 100 (e.g., between 1 in 100 and 1 in 10,000) (Kunreuther et al., 2001).

43 **2.2.4.5 Impact of uncertainty on coordination and cooperation**

44 Adaptation and especially mitigation responses require coordination and cooperation between
45 individuals, groups, or countries. The resulting outcomes of different joint actions are either
46 probabilistic or uncertain. Most theoretical and empirical work in game theory has been restricted to
47 deterministic outcomes, though recent experimental research on two person prisoners' dilemma
48 (PD) games shows that individuals are more likely to be cooperative when payoffs are deterministic
49 than when the outcomes are probabilistic. A key factor explaining this difference is that in a

1 deterministic PD game the losses of both persons will always be greater when they both do not
2 cooperate than when they do. When outcomes are stochastic there is some chance that the losses
3 will be smaller when both parties do not cooperate than when they do, even though the expected
4 losses to both players will be greater if they both decide not to cooperate than if they both
5 cooperate (Kunreuther et al., 2009).

6 In a related set of experiments, Gong et al. (2009) found that groups are less cooperative than
7 individuals in a two person deterministic PD game; however, in a stochastic PD game, where
8 defection increased uncertainty for both players, groups became more cooperative than they were
9 in a deterministic PD game and more cooperative than individuals in the stochastic PD game. These
10 findings have relevance to behaviour with respect to climate change where future outcomes of
11 specific policies are uncertain. When decisions are made by groups of individuals, such as when
12 delegations from countries are negotiating at the Conference of Parties (COP) to make commitments
13 for reducing GHG emissions where the impacts on climate change are uncertain, there is likely to be
14 more cooperation between the governments than if each country was represented by a single
15 decision-maker.

16 Cooperation also plays a crucial role in international climate agreements. There a growing body of
17 experimental literature looks at individuals' cooperation in the provision of climate change
18 mitigation under uncertainty. Tavoni et al. (2011) find that communication across individuals has a
19 key role in improving the likelihood of cooperation. Milinski et al., (2008) find that the higher the
20 risky losses associated with the failure to cooperate in the provision of a public good, the higher the
21 likelihood of cooperation. If the target for reducing CO₂ is uncertain, Dannenberg and Barrett (2012)
22 show in an experimental setting that cooperation is less likely than if the target is well-specified.

23 **2.3 Tools for improving decisions related to uncertainty and risk in climate** 24 **change**

25 This section examines the role that more formal models can play in assisting individuals,
26 organization, communities and countries in their decision making process with respect to climate
27 change policies when faced with the risk and uncertainties characterized in Sect. 2.1.1. In this sense
28 the tools discussed here can be used to facilitate System 2 behavior.

29 **2.3.1 Expected utility theory**

30 Expected utility [E(U)]theory (Ramsey, 1926; von Neumann and Morgenstern, 1944; Savage, 1954);
31 remains the standard approach for providing prescriptive guidelines against which other theories of
32 decision-making under risk and uncertainty are benchmarked. According to the E(U) model the
33 solution to a decision problem under uncertainty is reached by the following four steps:

- 34 I. Defining a set of possible decision alternatives
- 35 II. Quantifying uncertainties on possible states of the world
- 36 III. Valuing possible outcomes of the decision alternatives as utilities
- 37 IV. Choosing the alternative with the highest expected utility

38 This section clarifies the applicability of expected utility theory to the climate change problem,
39 highlighting its potentials and limitations.

40 **2.3.1.1 Elements of the theory**

41 EU theory is based on a set of axioms that are claimed to have normative rather than empirical
42 validity. Based on these axioms a person's subjective probability and utility functions can be
43 determined by observing preferences in structured choice situations. These axioms have been
44 debated, strengthened and relaxed for several generations: paradoxes have been generated and

1 debated, empirical studies performed and alternatives elaborated. Nonetheless these axioms
2 remain the basis for parsing decision problems in terms of probability and utility and seeking
3 solutions that maximize expected utility. Of course, it may someday be superseded.

4 **2.3.1.2 How can expected utility improve decision making under uncertainty?**

5 E(U) theory is a theory of individual choice: a farmer deciding what crops to plant or an entrepreneur
6 deciding whether to invest in wind technology. Such individuals apply E(U) theory by following the
7 four steps above. The risk perception and behavior described in Sect. 2.2 that often characterize
8 decision making do not preclude making good (or lucky) decisions. However, a structured approach
9 such as the E(U) model can reduce the impact of probabilistic biases and simplified decision rules
10 associated with System 1 behavior. At the same time the limitations of E(U) must be clearly
11 understood.

12 **Subjective versus objective probability**

13 In the standard E(U) model, each individual has his/her own subjective probability measure over the
14 set of possible worlds. Lay people are often inclined to defer to the views of experts, for questions
15 relating to their field of expertise. When the science 'isn't there yet' the experts won't have learned
16 sufficiently and their personal probabilities may diverge, perhaps substantially. In areas like climate
17 change, observed relative frequencies are always preferred when suitable sets of observations are
18 available. When observed relative frequencies are not available, uncertainty quantification must
19 have recourse to structured expert judgment (see section 2.3.6).

20 **Individual versus social choice**

21 In applying E(U) theory to problems of *social choice* a number of issues arise. Condorcet's
22 celebrated voting paradox (see Box) shows that groups of rational individuals deciding by majority
23 voting do not exhibit rational preferences. Decision conferencing under guidance of a skilled
24 facilitator sometimes brings stakeholders to adopt a common utility function. Unlike eliciting
25 probabilities, however, there is no formal mechanism like updating on observations to induce
26 agreement on utilities. Using a social utility or social welfare function to determine an optimal
27 course of action for society requires some method of measuring society's preferences. Absent that,
28 the social choice problem is not a simple problem of maximizing expected utility. A plurality of
29 approaches involving different aggregations of individual utilities and probabilities may best aid
30 decision makers. The basis and use of the social welfare function are discussed in Chapter 3 of
31 WGIII.

32 **Normative versus descriptive**

33 As noted, the rationality axioms of EU are claimed to have normative as opposed to empirical
34 validity. The paradoxes of Allais (1953) and Ellsberg (1961) reveal choice behaviour incompatible
35 with E(U); whether this requires modifications of the normative theory is a subject of debate.
36 McCrimmon (1968) found that business executives willingly corrected violations of the axioms, when
37 made aware of them. Other authors (Kahneman and Tversky, 1979; Schmeidler, 1989; Quiggin,
38 1993; Wakker, 2010) account for this choice behaviour by transforming the probabilities of
39 outcomes into "decision weight probabilities" which play the role of likelihood in computing optimal
40 choices but do not obey the laws of probability. Wakker (2010, p. 350) notes that decision weighting
41 also fails to describe empirically observed behaviour patterns. Whether decision makers *should*
42 evaluate emission scenarios with 'decision weight probabilities' is a case that remains to be made.

43

Box 2.1 Condorcet voting paradox

Suppose the next meeting of the Conference of Parties (COP) has three proposals for reducing greenhouse gas emissions: A, B and C and the preferences of three groups of countries having equal status are as follows:

Group	GHG Proposal		
	A	B	C
1	First	Second	Third
2	Second	Third	First
3	Third	First	Second

If C is chosen as the winner, it can be argued that B should win instead, since two groups of countries (1 and 3) prefer B to C and only one group (2) prefers C to B. However, by the same argument A is preferred to B, and C is preferred to A, by a margin of two to one on each occasion. The requirement of majority rule then provides no clear winner. Arrow's celebrated impossibility theorem (Arrow, 1951) strengthens this result by stating that, when voters have three or more distinct alternatives (options), no voting system can convert the ranked preferences of individuals into a community-wide (complete and transitive) ranking while also meeting a specific set of criteria.¹

2.3.2 Cost-benefit analysis and uncertainty**2.3.2.1 Elements of the theory**

Cost Benefit Analysis extends the concept that individuals make choices by comparing costs and benefits of different alternatives to the area of government decision-making. CBA does not address the challenges in achieving agreement across countries with respect to strategies for mitigating the impacts of climate change. For this reason it is a more appropriate technique to utilize by governmental units at the regional or national level. For example, a region could examine the benefits and costs over the next fifty years of building levees to reduce the likelihood and consequences of riverine flooding given projected sea level rise due to climate change. Nevertheless, CBA can still provide useful insights when applied to the global problem of climate mitigation as it can help assess the impact of proposed targets.

CBA is designed to select the alternative that has the highest social net present value based on an appropriate discount rate that converts future benefits and costs to their present values (Boardman et al., 2005). Social, rather than private, costs and benefits are compared including those affecting future generations (Brent, 2006). In this regard benefits across individuals are assumed to be additive. Distributional issues can be addressed by putting different weights on specific groups to reflect their relative importance. The challenges associated with the aggregation of individual welfare and with distributional issues are discussed at length in Chapter 3. The focus of CBA is on comparing the impact of different alternatives on outcomes. It does not explicitly evaluate different processes for making decisions at the community, regional or national level.

CBA can be extremely useful when dealing with well-defined problems that involve a limited numbers of actors as when choosing among different local mitigation or adaptation measures. It faces major challenges when defining the optimal level of global actions given the challenges of aggregating costs and avoided climate damages. Indeed, in order to compare all potential and actual costs and benefits to society of reducing climate change one has inevitably to deal with the issue of

¹ These criteria are unrestricted domain, non-dictatorship, Pareto efficiency and independence of irrelevant alternatives.

1 uncertainty of the projected impacts. It is here that integrated assessment models (IAMs) can play
2 an important role in providing a more structured approach to decision making by encouraging
3 System 2 behavior.

4 A large body of the integrated assessments of the optimal global level of mitigation deals with
5 uncertainty through extensive Monte Carlo CBA that involves simulating different scenarios (Tol,
6 2003 and; Dietz et al., 2007). Alternatively the problem can be formulated as a stochastic program
7 where agents hedge themselves against probabilistic outcomes (1991; Peck and Teisberg, 1993;
8 Kolstad, 1996; Nordhaus and Popp, 1997). In either case the decision maker is assumed to be
9 maximizing expected utility.

10 **2.3.2.2 How can CBA improve decision making under uncertainty**

11 Although cost-benefit analysis focuses on how specific policies impact on different stakeholders, it
12 assumes that the decision-maker will eventually make a choice after examining different
13 alternatives. To illustrate this point, consider a region that is considering developing ways for coastal
14 villages in hazard-prone areas to undertake measures for reducing future flood risks that are
15 expected to increase, in part due to sea level rise. Several different options are being considered
16 ranging from building a levee (at the community level) to providing low interest loans to encourage
17 residents and businesses in the community to invest in adaptation measures to reduce future
18 damage to their property (at the level of an individual decision maker).

19 Similar biases and heuristics discussed in the context of expected utility theory apply to cost-benefit
20 analysis under uncertainty. For example, the decision maker may be subject to the availability bias
21 and assume that their region will not be subject to flooding because there have been no floods in
22 the past 25 years. Decision-makers may also focus on short-time horizons, so that they do not want
23 to incur the high upfront costs associated with building flood protection measures such as dams or
24 levees because they consider only the expected benefits from the measures over the next several
25 years.

26 CBA can help overcome System 1 behavior by highlighting the importance of considering the
27 likelihood of events over time and the importance of exponential discounting over a long-term
28 horizon. In addition CBA can highlight the tradeoffs between efficient resource allocation and
29 distributional issues as a function of the weights assigned to different stakeholders (e.g. low income
30 households in flood prone areas).

31 **2.3.2.3 Advantages and limitations of CBA**

32 The main advantage of CBA in the context of climate change is that it is internally coherent and
33 based on axioms of rational behaviour. As prices used to aggregate costs and benefits are the result
34 of markets, CBA is in principle the best tool to represent people's preferences. Although the latter is
35 one of the main arguments in favour of CBA (Tol, 2003), the same argument is often used against
36 CBA by its opponents. Indeed, many impacts associated with climate change are hard to measure in
37 monetary terms and their omissions might mislead the cost-benefit balance. Also, weighing present-
38 day costs of mitigation against avoided damages in a far-distant future makes any CBA of the climate
39 problem very sensitive to the discount rate used to measure time preference, the choice and
40 interpretation of which is strongly debated.

41 The strongest and recurrent argument against CBA (Azar and Lindgren, 2003; Tol, 2003; Weitzman,
42 2009b, 2011; Nordhaus, 2011) is related to its failure to deal with low probability, catastrophic
43 events that might lead to unbounded measures of either costs and/or benefits. Under these
44 circumstances, typically referred to as "fat tails" events, CBA is unable to produce meaningful results
45 and more robust techniques are required. The debate concerning whether "fat tails" are indeed
46 relevant to the problem at stake is still unsettled (see for example (Pindyck, 2011)).

47 One way to address this problem is to leave off extremes when the consequences from these
48 outcomes do not demand serious consideration now. Specifically, this entails specifying a threshold

1 probability and a threshold loss, removing extremes that are below these values in determining risk
2 management strategies for dealing with climate change. Insurers and reinsurers utilize this
3 approach in determining the amount of coverage that they are willing to offer against a particular
4 risk. They diversify their portfolio of policies to keep the annual probability of a major loss below
5 some threshold level (e.g. 1 in 1000) (Kunreuther et al.). This behavior is in the spirit of a classic
6 paper by (Roy, 1952) on safety-first behavior. It was applied to environmental policy by Ciriacy-
7 Wantrup (1971) where he argues that “a *safe minimum standard* is frequently a valid and relevant
8 criterion for conservation policy.” (Ciriacy-Wantrup, 1971, p. 40). This procedure can be interpreted
9 as an application of probabilistic cost effectiveness analysis: chance constrained programming that is
10 discussed below.

11 **2.3.3 Cost-effectiveness analysis and uncertainty**

12 **2.3.3.1 Elements of the theory**

13 Cost-effectiveness analysis (CEA) is a tool based on constrained optimization for comparing policies
14 designed to meet a prespecified target. The target can be defined through a CBA, through the
15 application of a principle, e.g. the Precautionary principle, or some safety minimum standard, or it
16 could be funded in an ethical principle. The target could also be the result of the political and
17 societal negotiation processes. CEA is often used by Integrated Assessment models (IAMs) to
18 evaluate the costs of global/local climate policies. By means of Monte Carlo analysis, dynamic or
19 stochastic programming, or other computational techniques, CEA can examine the impacts of
20 uncertainty with respect to the cost of meeting a prespecified target and setting the target itself.

21 **2.3.3.2 How can CEA improve decision making under uncertainty?**

22 CEA helps decision makers to disentangle two sources of uncertainty: (1) the choice of target, mainly
23 based on the uncertainty of climate change impacts and (2) the uncertainty affecting policy
24 measures, investments costs, technological potentials and societal changes that are needed to reach
25 a specific target.

26 By simplifying the problem CEA should assist in overcoming biases related to assessing multiple and
27 contrasting sources of uncertainty. As expected utility is the basic concept underlying CEA under
28 uncertainty, advantages associated with expected utility itself, discussed in section 2.3.1, also apply.
29 To illustrate how CEA can be useful in this regard consider a national government that want to set a
30 target for reducing greenhouse gas emissions know there is uncertainty as to whether specific policy
31 measures will achieve the desired objectives. The uncertainties may be endogenous to the current
32 negotiation process or they may be related to proposed technological innovations. CEA could enable
33 the government to assess the optimal mitigation policy (or the optimal energy investment strategy)
34 for reducing GHG emissions in the face of this target uncertainty. Strategies with greater flexibility
35 (e.g. allowing for low cost retrofitting options) will be preferred under this type of analysis.

36 **2.3.3.3 Advantages and limitations of CEA over CBA**

37 For tackling the climate problem, the main advantages of CEA over CBA are: (i) it does not require
38 knowledge about climate damage functions that is currently being debated by experts, (ii) the
39 mitigation target is normally specified between now and 2050 so the relevant tradeoffs are confined
40 in time when weighing alternative energy system paths, than when having to further trade this off
41 against far-future avoided damages like in CBA. Hence, the results of CEA depend much less on the
42 pure rate of time preference than for CBA which considers costs and benefits in the more distant
43 future.

44 A drawback of CEA relative to CBA is that it does not enable one to undertake an integrated
45 valuation and comparison of benefits and costs. The choice of the target could in principle be
46 hostage to political decisions rather than people's preferences. However, once costs to society are

1 assessed and a range of targets are considered, this can be used as a basis to assess people's
2 preferences.

3 A further conceptual drawback of CEA comes when the technique is extended to cases in which the
4 target can only be observed probabilistically so that one utilizes techniques such as chance-
5 constrained programming (CCP) to evaluate alternative targets (Charnes and Cooper, 1959). A crucial
6 example are temperature targets which are related to emissions through fat-tailed climate
7 sensitivity so they cannot be observed with certainty (den Elzen and van Vuuren, 2007; Held et al.,
8 2009).

9 While CCP without learning is conceptually valid, the technique may run into inconsistencies when
10 anticipated learning is included in evaluating alternative policies (Eisner et al., 1971). If we anticipate
11 that climate sensitivity is 'large' or the target cannot be observed, it is infeasible to evaluate
12 alternative policies. For this reason, Schmidt et al., (2010) suggested adopting a linear version of
13 cost risk analysis (CRA) proposed by (Jagannathan, 1985) for the climate problem, a hybrid of CBA
14 and CEA. Although axiomatically, CRA belongs to the CBA-class, the damage function of CBA is
15 replaced by a willingness to accept a certain probability of exceeding a given climate target.

16 What does the use of CRA imply for evaluating policies for the climate problem as discussed in Sect.
17 2.4? As long as the major fat-tail effects are expected to lie at the climate sensitivity side, it means
18 that CEA would underestimate the required amount mitigation (as illustrated in the numerical
19 examples in 2.4.2), but would otherwise produce valid estimates. Future research needs to examine
20 the required additional mitigation investments when comparing deterministic and valid probabilistic
21 extensions of CEA under anticipated learning.

22 **2.3.4 The precautionary principle and robust decision making**

23 **2.3.4.1 Elements of the theory**

24 Any meaningful climate policy under the condition of uncertainty and anticipated learning will strive
25 for a decision-analytical framework that actively embraces the prospect of future learning, hence in
26 that sense it will be *adaptive*. If a precise probability measure and the consequences of proposed
27 actions for various states of the world were known to the decision maker (DM), then the Expected
28 Utility [E(U)] model can be used to determine a desirable adaptive policy. However if the DM has
29 the impression that at least one of these premises for EU_{max} is missing, alternative decision criteria
30 might become attractive, hereby implicitly sacrificing one or the other von Neumann-Morgenstern
31 axioms.

32 When the likelihood of specific events are highly uncertainty, often called 'deep uncertainty' or
33 'Knightian uncertainty' (Lange and Treich, 2008), the DM might utilize non-probabilistic decision
34 criteria such as minimax regret, maximin, or maximax. The precautionary principle (PP) is a version
35 of maximin. In its strongest form the PP implies that if an action or policy has a suspected risk of
36 causing harm to the public or to the environment, the burden of proof that it is *not* harmful falls on
37 those taking the action. An influential statement of the PP with respect to climate change is
38 principle 15 of the 1992 Rio Declaration on Environment and Development: "where there are threats
39 of serious or irreversible damage, lack of full scientific certainty shall not be used as a reason for
40 postponing cost-effective measures to prevent environmental degradation."

41 The PP allows policy makers to make discretionary decisions in situations where there is the
42 possibility of harm from taking a particular course or making a certain decision when extensive
43 scientific knowledge on the matter is lacking. The principle implies that there is a social responsibility
44 to protect the public from exposure to harm, when scientific investigation has found a plausible risk.
45 These protections can be relaxed only if further scientific findings emerge that provide sound
46 evidence that no harm will result.

1 Robust decision making (RDM) is a particular set of methods and tools developed over the last
2 decade to support decision-making and policy analysis under conditions of deep uncertainty and to
3 address the PP in a systematic manner. RDM uses ranges or, more formally, sets of plausible
4 probability distributions to describe deep uncertainty and to evaluate how well different policies
5 perform over the range of these probability distributions. Lempert et al. (2006) review the
6 application of robust approaches to decisions with respect to mitigating or adapting to climate
7 change.

8 Today's actions with respect to climate change affect the risks borne by future generations (e.g.
9 emissions today impacts on future environmental damage). This leads to what Gollier et al., (2000)
10 have termed the *precautionary effect*. It can be shown that this effect is consistent with a reduction
11 of current risk-exposure only under some specific and often restrictive conditions on the utility and
12 damage functions (Ulph and Ulph, 1997). Therefore the theory of option values cannot be used to
13 argue that scientific uncertainty should affect current CO2 emissions in any specific direction. Finally,
14 aversion against intertemporal consumption uncertainty introduces a new normative degree of
15 freedom to EUmax that may lead to lower optimal future emissions. (Traeger, 2009). Future work
16 needs to examine whether this finding implies that one should evaluate policies using very low pure
17 rates of time preference which in turn could be interpreted as a weak form of the precautionary
18 principle.

19 **2.3.4.2 How can RDM improve decision making under uncertainty?**

20 RDM enables the decision maker to determine how well a set of alternative strategies including
21 maintaining the status quo perform under different scenarios. To illustrate this point, consider a
22 government agency that is developing a strategy for renewable energy to meet its country's
23 greenhouse gas (GHG) reduction goals. RDM can examine a wide range of climate change scenarios
24 based on estimates from the scientific community to see the impact of different renewable energy
25 strategies on GHG emissions. The precautionary principle would require the government agency to
26 examine the worst case scenario and utilize a strategy that was optimal for this specific case --- in
27 other words, utilize a minimax approach to the problem.

28 **2.3.4.3 Advantages and limitations of RDM**

29 RDM enables the decision maker to make tradeoffs between following a minimax solution based on
30 the PP or utilizing a strategy that performs well under a wide variety of scenarios regarding climate
31 change. Future work has to show to what extent RDM can address the challenges posed by
32 Weitzman (2009b) and others with respect to fat tails.

33 **2.3.5 Adaptive management**

34 Adaptive management is an approach to governance that explicitly incorporates mechanisms for
35 reducing uncertainty over time, growing out of the field of conservation ecology in the 1970's
36 (Holling and others, 1978; Walters and Hilborn, 1978). Two strands of adaptive management have
37 been developed for improving decision-making uncertainty: *passive* and *active*. *Passive adaptive*
38 *management (PAM)* involves carefully designing monitoring systems, at the relevant spatial scales,
39 so as to be able to track the performance of policy interventions and improve them over time in
40 response to what has been learned. *Active adaptive management (AAM)* extends PAM by designing
41 the interventions themselves as controlled experiments, so as to generate new knowledge. For
42 example, if a number of political jurisdictions were seeking to implement support mechanisms for
43 technology deployment, in an AAM approach they would deliberately design their separate
44 mechanisms somewhat differently from each other, recognizing that some mechanisms will
45 underperform relative to others. By introducing such variance into the management regime,
46 however, they would collectively learn more about how industry and investors respond to a range of
47 interventions. All jurisdictions could then use this knowledge in a later round of policy-making.

1 Among individuals in System 1 mode, both status quo bias (whereby individuals have a preference
2 for the familiar) and omission bias (whereby individuals attach more personal blame to errors of
3 commission rather than omission) hinder the kind of experimentation and risk taking that lead to
4 new knowledge (Samuelson and Zeckhauser, 1988; Baron and Ritov, 1994). In theory, adaptive
5 management ought to correct for this problem, by explicitly incorporating a learning dimension into
6 policy-making. Illustrating this, Lee (1993) presented a paradigmatic case of active adaptive
7 management in the effort to increase salmon stocks in the Columbia River watershed in the western
8 United States and Canada. Here, there was the opportunity to introduce a number of different
9 management regimes on the individual river tributaries, and through a comparison of the effects,
10 reduce uncertainty about salmon population dynamics. In practice, adaptive management can easily
11 fall victim to institutional dynamics. As Lee (1993) documented, policy-makers on the Columbia River
12 were ultimately not able to carry through with adaptive management; local constituencies, valuing
13 their own immediate interests over long-term learning in the entire region, played a crucial role in
14 blocking it.

15 In the area of climate change, there are no documented cases in the literature of AAM, but it is easy
16 to consider the information gathering and reporting requirements of the UNFCCC as reflecting PAM
17 insights into policy design. It is also easy to consider the diversity of approaches implemented for
18 renewable energy support across the states and provinces of North America and the countries in
19 Europe in this respect. In these cases, there was no deliberate intention to introduce variance in the
20 management regime. The combination of the variance in action with data gathered about the
21 consequences of these actions by government agencies has allowed for robust analysis on the
22 relative effectiveness of different instruments (Blok, 2006; Mendonça, 2007; Butler and Neuhoff,
23 2008).

24

25 **Box 2.2** Quantifying uncertainty

26 Natural language is not adequate for propagating and communicating uncertainty. To illustrate
27 consider the US National Research Council 2010 report *Advancing the Science of Climate Change*
28 (*America's Climate Choices: Panel on Advancing the Science of Climate Change; National Research*
29 *Council, 2010*). Using the IPCC AR4 calibrated uncertainty language, the report bases its first
30 summary conclusion on “high or very high confidence” in six statements (p.4,5). Paraphrasing the
31 first two, the NRC is highly confident that (1) the Earth is warming, they are also highly confident
32 that (2) most of the recent warming is due to human activities. What does the second statement
33 mean? Does it mean they are highly confident that the Earth is warming AND the recent warming is
34 human caused, or given that the Earth is warming they are highly confident this warming is human
35 caused? The latter seems most natural, as the warming is asserted in the first statement. In that
36 case the “high confidence” applies to a conditional statement. The probability of both statements
37 being true is the probability of the condition (Earth is warming) multiplied by probability of human
38 cause, given that warming is taking place. If both statements enjoy high confidence, then in the
39 calibrated language of AR4 the statement that both are true would only be “more likely than not”
40 ($0.8 \times 0.8 = 0.64$). If five logically independent statements each hold with probability 0.8, the probability
41 that all of them hold can be anything from 0.8 to 0. Qualitative uncertainty analysis easily leads the
42 unwary to erroneous conclusions. Interval analysis is a semi-qualitative method in which ranges are
43 assigned to uncertain variables without distributions and can mask the complexities of propagation.
44 People without System 2 training in uncertainty quantification will necessarily reason about
45 uncertainty in the natural language; the uncertainty analyst's task is to help them avoid the pitfalls.

46 **2.3.6** Uncertainty analysis techniques

47 Uncertainty analysis consists of both qualitative and quantitative methodologies. A Qualitative
48 Uncertainty Analysis (QLUA) provides an initial step in improving the choice process of decision
49 makers by providing data in a form that individuals can easily understand. QUA normally does not

1 require complex calculations so that it can be useful in overcoming judgmental biases that
2 characterize System 1 behavior. QJUA assembles arguments and evidence and provides a verbal
3 assessment of plausibility, frequently placed in a Weight of Evidence narrative. A quantitative
4 uncertainty analysis (QJUA) assigns a joint distribution to uncertain parameters yielding a joint
5 distribution with respect to input and output of a specific model used to characterize specific
6 phenomena. QJUA was pioneered in the nuclear sector in 1975 (Rasmussen, 1975) to determine
7 the risks associated with nuclear power plants. Cooke (2012) reviews the development of QJUA and
8 its prospects for application to climate change.

9 **2.3.6.1 Structured expert judgment**

10 Structured expert judgment designates methods in which experts quantify their uncertainties on
11 variables from their field to build probabilistic input for complex decision problems (Morgan and
12 Henrion, 1990; Cooke, 1991; O’Hagan, 2006). A wide variety of activities falls under the looser
13 appellation “expert judgment,” including blue ribbon panels, Delphi surveys and decision
14 conferencing.

15 **Elements**

16 Structured expert judgment as science based uncertainty quantification was pioneered in the
17 Rasmussen Report on risks of nuclear power plants (Rasmussen, 1975), and the methodology was
18 further elaborated in successive studies. The most recent benchmark involves treating experts as
19 statistical hypotheses whose performance is evaluated in terms of statistical likelihood and
20 informativeness. The performance evaluation is based on assessments of variables from their field
21 whose true values are known post hoc. Protocols for expert selection and training, elicitation
22 procedures and performance-based combinations are also formulated (see special issue *Radiation*
23 *Protection Dosimetry* (Goossens et al., 2000)). If expert performance is not validated, then the
24 experts’ distributions are combined with equal weighting or not combined. In large studies, multiple
25 expert panels provide inputs to large computer models, and there is no practical alternative to
26 combining expert judgments except to use equal weighting. Hora (2004) showed that equal weight
27 combinations of statistically accurate (“well calibrated”) experts, loses statistical accuracy.
28 Performance based combinations have performed well in practice (Cooke and Goossens, 2008;
29 Aspinall, 2010).

30 **How can this tool improve decision making under uncertainty?**

31 Structured expert judgment can provide insights into the nature of the uncertainties associated with
32 a specific risk and the importance of undertaking more detailed analyses in the spirit of System 2
33 behavior in order to design meaningful strategies and policies for dealing with climate change.
34 Structured expert judgment has migrated into many fields including volcanology (Aspinall, 1996,
35 2010), dam dyke/safety (Aspinall, 2010), seismicity (Klügel, 2008), civil aviation (Ale et al., 2009),
36 ecology (Martin et al., 2012; Rothlisberger et al., 2012), toxicology (Tyshenko et al., 2011), security
37 (Ryan et al., 2012) and epidemiology (Tuomisto et al., 2008) in addition to climate change (Morgan
38 and Keith, 1995; Zickfeld et al., 2010).

39 General conclusions from the experience to date are: (1) formalizing the expert judgment process
40 and adhering to a strict protocol adds substantial value to understanding the importance of
41 characterizing uncertainty, (2) experts differ greatly in their ability to give statistically accurate and
42 informative uncertainty quantifications, and (3) if expert judgments must be combined to support
43 complex decision problems, the method of combination should be subjected to the same quality
44 controls as the experts themselves (Aspinall, 2010). As attested by a number of governmental
45 guidelines and high visibility applications, structured expert judgment is increasingly accepted as
46 “quality science” that is applicable when other methods are unavailable (U.S. Environmental
47 Protection Agency, 2005). Climate science has also seen some application of structured expert
48 judgment and some less formal applications (Nordhaus, 1994; Weitzman, 2001).

1 To illustrate the use of structured expert judgment in the context of climate change, damages or
2 benefits to ecosystems from invasions of non-indigenous species are impossible to quantify and
3 monetize on the basis historical data. However ecologists, biologists and conservation economists
4 have substantial knowledge regarding the possible impacts of invasive species. Recent studies
5 (Rothlisberger et al., 2009, 2012) applied structured expert judgment with a performance-based
6 combination and validation to quantify the costs and benefits of the invasives introduced since 1959
7 into the U.S. Great Lakes by opening the St. Lawrence seaway. Nine experts assessed 12 calibration
8 variables relating to near future fishing effort and catches. Combining the experts' assessments with
9 equal weight yielded poor statistical behaviour, but the combination based on performance yielded
10 satisfactory statistical results. For the U.S. waters, median damages aggregated across multiple
11 ecosystem services were \$138 million per year, and there is a 5% chance that for sport fishing alone
12 losses exceeded \$800 million annually. Lessons from such studies are (1) the existence of large
13 uncertainties need not paralyse quantitative analysis, (2) experts may have applicable knowledge
14 that can be captured in a structured elicitation and (3) statistical validation of experts and
15 combinations of experts is possible.

16 **Advantages and limitations of structured expert judgment**

17 Expert judgment studies do not reduce uncertainty; they merely quantify it. If the uncertainties are
18 large, as indeed they often are, then decision makers hoping that science will relieve them of the
19 burden of deciding under uncertainty may be disappointed. Since its inception, structured expert
20 judgment has met skepticism in some quarters, as it is, after all, just opinions and not hard facts. Its
21 steady growth and widening acceptance over 35 years correlates with the growth of complex
22 decision support models which outstrip conventional data resources. Structured expert judgment
23 provides some measure of validated quantitative input in these contexts, but it must never justify a
24 diminution of effort for collecting hard data.

25 **2.3.6.2 Scenario analysis and ensembles**

26 Scenario analysis develops a set of possible futures, which are based on extrapolating current trends,
27 and varying key parameters, without sampling in systematic manner from an uncertainty
28 distribution. Scenarios often look at a long time horizons so they capture structural changes. The
29 futurist Herman Kahn and colleagues at the RAND Corporation are usually credited with inventing
30 scenario analysis (Kahn and Wiener, 1967). In the climate change arena, scenarios are often
31 presented as different emission pathways. Predicting the effects of an emission pathway involves
32 modeling the earth's response to the forcing from anthropogenic greenhouse gases, in combination
33 with other known forcings and responses. Different climate models will yield different predictions
34 for the same emission scenario.

35 **Elements of the theory**

36 In classical scenario analysis, current trends are identified and extrapolated into the future to
37 determine a "surprise free scenario". Canonical variations are then projected by changing
38 parameters in the surprise free scenario. Unknown parameters are often fed extreme values,
39 usually one at a time, with the intention of circumscribing the space of possibilities.

40 With respect to climate change, the Model Intercomparison study of scenarios reported by Meehl et
41 al.(2007) included several SRES emissions paths, and a "climate sensitivity experiment"
42 (instantaneously doubling CO₂ and running to equilibrium). This selection of scenarios contains no
43 suggestion regarding their realism or relative likelihood. Ensembles of model runs generated by
44 different models are sometimes called multimodel ensembles or super-ensembles.

45 **How can scenario analysis improve decision making under uncertainty?**

46 Scenario analysis is an essential step in scoping the range of effects of human actions and climate
47 change and spurs further research. Climate scenarios have been used to estimate the natural
48 climate variability in detecting climate change and attributing this change to human activity. An

1 optimal signal for detecting climate change takes the natural variability of the signal's components
2 into account. Since the historical record is too short to assess this variability, long term multimodel
3 ensembles are used (Zhang et al., 2007).

4 **Advantages and limitation of scenario analysis**

5 The advantage of scenario / ensemble analyses is that they can be performed without quantifying
6 uncertainty on the underlying unknown parameters. On the downside, it is easy to read more into
7 these analyses than is justified. Analysts often forget that scenarios are illustrative possible futures
8 along a continuum. They tend to use one of those scenarios in a deterministic fashion without
9 recognizing that they have a low probability of occurrence and are only one of many possible
10 outcomes. As pointed out in Hansen et al., (2011) many of these models have common ancestors,
11 creating dependences between different model runs.

12 **2.4 Risk and uncertainty in climate change policy issues**

13 **2.4.1 Guidelines for developing policies**

14 There is a rich literature and body of practice on policy development, providing guidance on issues
15 such as identifying appropriate social objectives, prioritizing between competing priorities (such as
16 equity and efficiency), and designing particular governmental interventions in society—policy
17 instruments—to achieve particular outcomes.

18 A cross-cutting theme is that of risk and uncertainty, for at least four reasons. First, the relative
19 ranking of different policy instruments may be sensitive to existing uncertainties, requiring analysis
20 of multiple possible outcomes. Second, some policy instruments can have the effect of introducing
21 new uncertainties that some actors will face, which need to be taken into account. Third, parties and
22 stakeholders involved in political decision-making may find particular risks or negative outcomes
23 especially unattractive, to be avoided at all costs. As the groups of actors and the choices they face
24 change over time, the kinds of risks and uncertainties that matter for policy-making are also likely to
25 evolve.

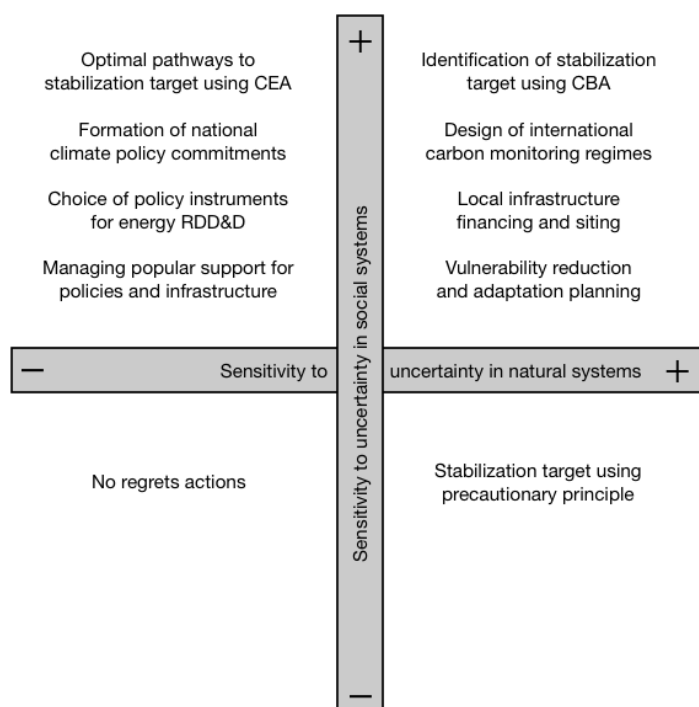
26 Indeed this is the case for climate policy. First, there has been a widening of the governance forums
27 within which climate policies have been developed and enforced, from the international across
28 multiple multilateral forums (Victor, 2011), to multiple networks within nation states (Andonova et
29 al., 2009; Hoffmann, 2011), to subnational jurisdictions such as states, counties, and cities (Moser,
30 2007; Bulkeley, 2010).

31 Second, there has been an expansion in the types of actors playing a visible role in influencing
32 government policy, including civil society (Cabré, 2011), finance and business organizations
33 (Meckling, 2011), and high profile concerned individuals, such as actors and celebrities (Boykoff and
34 Goodman, 2009).

35 Third the number of different policy instruments under active discussion has also increased, from a
36 focus on cap and trade instruments (Betsill and Hoffmann, 2011; Hoffmann, 2011), to now include
37 instruments such as feed-in tariffs or quotas for renewable energy (Wiser et al., 2005; Mendonça,
38 2007), investments in research and development (Sagar and van der Zwaan, 2006; De Coninck et al.,
39 2008; Grubler and Riahi, 2010), or reform of intellectual property laws (Dechezleprêtre et al., 2011;
40 Percival and Miller, 2011)

41 Fourth, there has been a greater effort to find synergies between climate policy and other policy
42 objectives, meaning that consideration of multiple benefits of a single policy instrument is now
43 important. For example, efforts to protect tropical rainforests (McDermott et al., 2011), rural
44 livelihoods (Lawlor et al., 2010), biodiversity (Jinnah, 2011), public health (Stevenson, 2010), fisheries
45 (Axelrod, 2011), arable land (Conliffe, 2011), energy security (Battaglini et al., 2009), and job creation
46 (Barry et al., 2008) have been framed as being additionally justified by climate change concerns.

1 The expansion of the number of climate policy issues alters the characterization of which
 2 uncertainties matter. Figure 2 summarizes these sensitivities, grouping the types of uncertainty into
 3 those associated with natural systems (e.g., climate, oceans, glaciers, or habitats) and social systems
 4 (e.g., the economy, population, technologies, or preferences).



5

6

Figure 2.2 [Note of the TSU: Figure caption missing]

7 To date the literature on the role that risk and uncertainty play in climate change policy has assumed
 8 that the relevant stakeholders are making decisions by undertaking complex calculations as
 9 characterized by System 2 behavior. There has been limited attention given to the judgmental
 10 biases and simplified decision rules that are likely to be present in System 1 thinking. For example, if
 11 a decision maker is myopic and focuses on short-term horizons then s/he may not choose the
 12 alternative that appears optimal on the basis of a systematic analysis of long-term costs and
 13 benefits. For example, installing an energy efficient appliance may not be adopted if one focuses on
 14 a payback period of the next two years even though the decision maker is convinced that he will be
 15 using the appliance for at least the next five years. The discussion of climate change policies in this
 16 section will examine the analyses that have been undertaken using models of choice discussed in
 17 Sect. 2.5 "Future Research Directions." Sect. 2.5 proposes studies that examine how perception and
 18 behavioural responses to risk and uncertainty influences policy and how System 2 behavior can
 19 improve the process.

20 Nearly all policy actions are sensitive to uncertainties in social systems, and many are sensitive to
 21 uncertainties in natural systems. The establishment of a stabilization target using the precautionary
 22 principle, is one policy issue that appears to be sensitive to uncertainties in natural systems alone. In
 23 the following subsections we consider these different types of policy choices. To provide structure,
 24 we order the different policy issues from the most global and abstract to the most local and
 25 concrete.

26 **2.4.2 Optimal or efficient stabilization pathways (social planner perspective) under** 27 **uncertainty**

28 Integrated assessment models (IAM) are tools capable of representing the interplay of economic
 29 activities, other human activities and the dynamics of the natural system in response to various
 30 choices open to society. In IAM models a representative agent (social planner), who is modelled as a

1 System 2 decision maker undertaking complex computations, maximizes intertemporal aggregate
 2 welfare or minimizes total costs to society to reach a prespecified target. Structures and calibration
 3 procedures of IAM models are described in detail in Chapter 6. Here we focus on IAM results that
 4 acknowledge uncertainty as an integrated part of the decision-analytic framework or examine the
 5 effect of variations in uncertain parameters' values through Monte-Carlo analysis.

6 Climate policy uncertainty has to be considered in the light of climate and technology policy
 7 uncertainty in order to have a realistic representation of the problem. The few analyses where
 8 uncertainty is considered typically involve simplified IAMs and have not incorporated scenarios (see
 9 Moss et al., 2010 for an example). The key question these analyses address is how uncertainty alters
 10 the optimal social planner's short term reaction to climate change. A subset also asks whether
 11 adjusting behaviour to uncertainty and designing more flexible policies and technology solutions
 12 would induce a significant welfare gain.

13 Table 1 provides an overview of the existing literature by categorizing uncertainty and listing the
 14 published studies under each heading. We also distinguish whether each study reported a positive,
 15 negative or ambiguous effect of uncertainty on short-term mitigation action. There appear to be
 16 consensus in the literature that the inclusion of uncertainty implies a more significant short term
 17 response to climate change. An important exception arises only when continuous damage
 18 uncertainty is considered. In this case an ambiguous or negative impact on early mitigation action
 19 predominates. Although studies differ in their approaches, the main underlying reason for not taking
 20 short term action is when the irreversible sunk cost investment in abatement options outweighs the
 21 irreversible effect of climate change. This is particularly relevant in studies where
 22 catastrophic/threshold damage is not included in the picture and no consideration is given to the
 23 non-climate related benefits of these investments such as enhancing energy security.

24 **Table 2.1** Overview of literature on integrated assessment models examining mitigation actions

		Effect on Mitigation Action					
		<i>Accelerates / Increases Mitigation Action</i>		<i>Delays / Decreases Mitigation Action</i>		<i>Ambiguous Effect</i>	
		Number of Papers	References	Number of Papers	References	Number of Papers	References
Type of Uncertainty Considered	<i>Up Stream (emission drivers)</i>	6	Rozenberg et al. (2010), Kelly and Kolstad (2001), Cooke (2012), O'Neill et al. (2008), Webster et al. (2002), Reilly et al. (1987)	0		0	
	<i>Down Stream (climate and damages) - Continuous</i>	3	Athanassoglou & Xepapadeas (2011), Peck & Teisberg (1994), Chichilnisky and Heal (1993).	3	Baranzini et al. (2003), Kolstad (1996a), Kolstad (1994)	10	Kolstad (1996b), Ulph & Ulph (2012), Fisher & Narain (2003), Gollier et al. (2000), Lange and Treich (2008), Tsur and Zemel (1996), Clarke and Reed (1994), Ha-Duong and Treich (2004), Baker et al. (2006), Lorenz et al. (2012).
	<i>Down Stream (climate and damages) - Catastrophic event</i>	15	Baranzini et al. (2003), Dumas & Ha-Duong (2005), Gjerde et al. (1999), O'Neill & Oppenheimer (2002), Ha-Duong (1998), McInerney & Keller (2008), Hope (2008), Lorenz et al. (2012b), De Zeeuw & Zemel (2012), Gollier and Treich (2003), Heal (1984), Tsur and Zemel (2009), Funke & Paetz (2011), Webster et al. (2008), Inversion and Perrings (2012).	1	Peck & Teisberg (1995)	0	
	<i>Policy Response</i>	6	Bosetti et al. (2009), Ha-Duong et al. (1997), Farzin & Kort (2000), Bosetti & Tavoni (2009), Blanford (2009), Durand-Lasserve et al. (2010)	2	Baker & Shittu (2006), Baudry (2000)	0	
	<i>Multiple sources of Uncertainty</i>	14	Held et al. (2009), Keller et al. (2004), Pizer (1999), Tol (1999), Yohe et al. (2004), Obersteiner et al. (2001), Labriet et al. (2010), Grubb (1997), Nordhaus (1994) Nordhaus & Popp (1997), Bahn et al. (2008), Hope (2009), Baker & Shittu (2008) Baker &	1	Scott et al. (1999)	1	Manne & Richels (1991)

25

1 Although IAMs mimic System 2 decision makers, in reality social planners might resort to System 1
2 processes to simplify their decision processes, leading to biases and inferior choices. To date there is
3 no research that considers such behaviour by decision makers and examines how it relates to the
4 optimal projections of IAMs. We discuss the need for such studies in the concluding section on
5 Future Research.

6 **2.4.2.1 Analyses predominantly addressing climate or damage response uncertainty**

7 In determining what uncertainty has an impact on optimal mitigation effort and whether learning
8 changes the result and the corresponding expected welfare, the answers strongly correlate with a
9 classification in terms of the following four decision frameworks: (i) CBA for only mildly nonlinear
10 damages (with respect to temperature forcing) (see Table 1, 'Downstream - continuous') , (ii) CBA
11 for strongly nonlinear damages such as tipping points (see Table 1, 'Downstream – catastrophic
12 events'), (iii) CEA employing a temperature target or avoided tipping point target (distributed in that
13 Table among 'Downstream – catastrophic events' and 'Multiple sources of uncertainty'), and (iv) any
14 other 'beyond probability'-criterion such as Knightian uncertainty or purely deterministic criteria in
15 combination with a precautionary or minimum regret attitude (to be found in the 'Downstream –
16 catastrophic events' section of the Table).

17 In class (i), the effect of uncertainty is ambiguous: the literature displays effects between an
18 increased (e.g., Athanassoglou and Xepapadeas, 2011) to a decreased optimal mitigation effort (see
19 Table 1). While uncertainty in combination with convex damages suggests an enhanced mitigation
20 effort, Lorenz et al. (Hof et al., 2010) show how this effect is often compensated by other
21 nonlinearities in IAMs. The effects of uncertainty also depend on whether uncertainty can be
22 expected to be reduced (Kelly and Kolstad, 1999).

23 In class (ii), uncertainty generically leads to more stringent optimal mitigation, although the effect
24 might be minor if damages lie far in the future (McInerney and Keller, 2007). In class (iii), uncertainty
25 strongly acts towards more mitigation if a security level for observing the target of markedly larger
26 than 50% is assumed (McInerney and Keller, 2007; Held et al., 2009). If a security level of 100% is
27 modelled, the effect of learning on the mitigation effort can also be studied. Webster et al. (2008)
28 find that expected learning can reduce the mitigation effort. Class (iv) is generically characterized
29 by a high-end mitigation recommendation (see e.g., Hof et al., 2010; Funke and Paetz, 2011).

30 **2.4.2.2 Analyses predominantly addressing policy responses uncertainty**

31 Research in this area has focused on two main strands: one examining the impact of the uncertain
32 effectiveness of Research, Development and Demonstration (RD&D) and/or of the future cost of
33 technologies in reducing the impact of climate change. An example of this would be, the optimal
34 investment in energy technologies that a social planner should undertake knowing that there might
35 be a nuclear ban in the near future. The second strand looks at the uncertainty concerning future
36 climate policy instruments and stringency with some attention given to climate and/or damage
37 uncertainty in some studies. An example is the optimal technological mix in the power sector to
38 hedge uncertainty related to the stringency of climate policy in 2020.

39 With respect to the first strand of research the main challenge is to quantify uncertainty related to
40 the future costs of mitigation technologies. Indeed, there does not appear to be a single stochastic
41 process that underlies all (RD&D) programs or the process of innovation. Thus elicitation of expert
42 judgment on the probabilistic improvements in technology performance and cost becomes a crucial
43 prerequisite for numerical analysis. A literature is emerging (see for example Baker et al., 2008;
44 Curtright et al., 2008; Chan et al., 2010; Baker and Keisler, 2011), that uses expert elicitation to
45 investigate the uncertain effects of RD&D investments on the prospect of success of mitigation
46 technologies. In future years, this will allow the emergence of a literature studying the probabilistic
47 relationship between R&D and the future cost of energy technologies in IAMs. The very few existing
48 papers reported in Table 1 under the Policy Response uncertainty column(see Blanford, 2009;

1 Bosetti and Tavoni, 2009) point to an increased action in response to uncertainty, both in terms of
2 investments in energy RD&D and investments in early deployment of carbon free energy
3 technologies.

4 Turning to the second strand of literature reported in the Policy Response or in the Multiple
5 Uncertainty columns of Table 1 (see Ha-Duong et al., 1997; Baker and Shittu, 2006; Durand-Lasserve
6 et al., 2010), most analyses imply increased mitigation in the short term when there is uncertainty
7 about future policy stringency due to the asymmetry of future states of nature: the “no policy” case
8 implies losses of carbon free capital are outweighed by the potential losses of a delayed and
9 extremely fast decarbonisation that would be required if a “stringent climate policy” state of nature
10 were realized.

11 **2.4.2.3 Future development pathways**

12 Uncertainty should play a larger role than it currently has in creating plausible scenarios to
13 investigate the drivers of climate change. Different assumptions on population trends, human
14 activities, technology adoption, natural resource exhaustion might indeed lead to very different
15 futures, independent of climate mitigation. The integration of physical, biological and social
16 dimensions of the problem will be at the heart of the development of a new family of Shared Socio
17 Economic Pathways that will update the SRES, Moss et al. (2010).

18 **2.4.3 International negotiations and agreements under uncertainty**

19 Social planner studies, as reviewed in the previous sub-sections, consider the appropriate magnitude
20 and pace of aggregate global emissions reduction. These issues have been the subject of
21 negotiations at the international level along with the structuring of national commitments and the
22 design of mechanisms for compliance, monitoring and enforcement.

23 **2.4.3.1 Treaty formation**

24 There exists a vast literature looking at international treaties in general and how they might be
25 affected by uncertainties. Cooper (1989) has examined two centuries of international treaties to
26 control the spread of communicable diseases and concludes that it is only when uncertainty is
27 largely resolved will countries enter into international treaties. Young (1994), on the other hand,
28 suggests that it may be easier to enter into treaties when parties are uncertain as their individual net
29 benefits from an agreement than when that uncertainty has been resolved. Coalition theory predicts
30 that with respect to international negotiations on a global externality such as climate change, stable
31 coalitions will be generally small and/or ineffective (see for example Barrett, 1994).

32 Relatively little research has been undertaken on the effect of uncertainty on the stability of
33 multilateral environmental agreements (MEAs) and when uncertainty and learning has the potential
34 to unravel agreements. Kolstad (2007), using a game theoretic model, looks specifically at
35 environmental agreements and investigates the extent to which the size of the largest stable
36 coalition changes as a result of learning and systematic uncertainty. He finds that that systematic
37 uncertainty by itself decreases the size of an MEA. Kolstad and Ulph (2008) show that partial or
38 complete learning has a negative impact on the formation of an MEA since it reduces the welfare
39 benefits to some countries from joining a coalition and hence reduces the number of countries who
40 are viable candidates for the MEA. Baker (2005), using a model of the impacts of uncertainty and
41 learning in a non-cooperative game, shows that the level of correlation of damages across countries
42 is a crucial determinant of outcome.

43 The role of catastrophic, low probability events on the likelihood of cooperation towards a global
44 climate agreement has been investigated in Barrett (2011). By comparing a cooperative agreement
45 with the Nash equilibrium it is possible to assess a country's incentives to participate in an
46 international climate agreement. As noted by Heal and Kunreuther (2011), the signing of the
47 Montreal Protocol by the United States led many other countries to follow suit. They utilize the
48 lessons from the Montreal Protocol to suggest how it could be applied to foster an international

1 treaty on greenhouse gas emissions by tipping a non-cooperative game from an inefficient to an
2 efficient equilibrium.

3 Several analyses, including Victor (2011) and Hafner-Burton et al. (2012), suggest that the likelihood
4 of a successful comprehensive international agreement for climate change is low, because of the
5 sensitivity of negotiations to uncertain factors, such as the precise alignment and actions of
6 participants. Keohane and Victor (2011), in turn, suggest that the chances of a positive outcome
7 would be higher in the case of numerous, more limited agreements.

8 **2.4.3.2 Strength and form of national commitments**

9 Buys et al. (2009) construct a model to predict national level support for a strong global treaty based
10 on the risks that they face domestically by distinguishing between vulnerabilities to climate impacts
11 on the one hand, and climate policy constrictions with respect to fuel sources on the other. They
12 suggest that countries would be most supportive of strong national commitments when their impact
13 vulnerability is high but their source vulnerability low, and least supportive in the reverse case. They
14 do not, however, test their model empirically.

15 Victor (2011) analyzes the structure of the commitments themselves, or what Hafner-Burton et al.
16 (2012) call rational design choices. Victor suggests that while policy makers have considerable
17 control over the carbon intensity of their economies, they have much less control over the
18 underlying economic growth of their country. As a result, there is greater uncertainty for absolute
19 emissions reductions, which depend on both factors than for reductions in carbon intensity alone.
20 Victor suggested that this could account for a reluctance of many countries to make strong binding
21 commitments for absolute emissions reductions. Consistent with this reasoning, Thompson (2010)
22 examined negotiations within the UNFCCC at two points in time, and found limited qualitative
23 support for the hypothesis that uncertainty with respect to national emissions was associated with
24 greater support for flexibility in terms of the type of national commitment and/or the means of
25 satisfying it.

26 Webster et al. (2010) examined whether uncertainty increases the potential for individual countries
27 to hedge with respect to joining an international trade agreement. They found that hedging had a
28 minor impact compared to the other effects of international trading, namely burden sharing and
29 wealth transfer. These findings may have relevance for structuring a carbon market to reduce
30 emissions to take advantage of disparities in marginal abatement costs across different actors. In
31 theory, the right to trade emission permits or credits could lessen the uncertainties associated with
32 any given actor's compliance costs compared to the case where no trading were possible. Under a
33 trading scheme if an actor discovered its own compliance costs to be exceptionally high, for
34 example, it could purchase credits on the market.

35 **2.4.3.3 Design of monitoring and verification regimes**

36 A particular issue in climate treaty formation is uncertainty with respect to actual emissions from
37 industry and land use. Monitoring, reporting, and verification (MRV) regimes have the potential to
38 set incentives for participation and still be stringent, robust and credible. Problems are created
39 because estimating emissions, especially in the land use sector in many developing countries, is so
40 uncertain that the effects of changes in the management of emissions could remain within error
41 bounds and would thus be undetectable. Researchers have suggested that the carbon source that is
42 most problematic from the MRV perspective, is soil carbon (Bucki et al., 2012).

43 In the near term, requiring an MRV regime of the highest standards and accuracy could require data
44 available only in wealthy countries, and thus have the impact of excluding least developed countries
45 from participating (Oliveira et al., 2007). By contrast, there are design options for MRV regimes that
46 are less accurate, but which still address the drivers of emissions. By being more inclusive these
47 options could be a more effective way to actually reduce emissions in the near term (Bucki et al.,
48 2012).

1 In the longer term, robust and harmonised estimation of emissions and removals in agriculture and
2 forestry requires investment in monitoring and reporting capacity, especially in developing countries
3 (Böttcher et al., 2009; Romijn et al., 2012). Reflecting this need for an evolving MRV regime to match
4 data availability, the 2006 Guidelines for National Greenhouse Gas Inventories, prepared by an IPCC
5 working group, suggested three hierarchical tiers of data for emission and carbon stock change
6 factors with increasing levels of data requirements and analytical complexity. These range from tier
7 1 (using IPCC default values of high uncertainty) to tier 2 (using country-specific data) and tier 3
8 (using higher spatial resolution, models, inventories). In 2008, only Mexico, India and Brazil had the
9 capacity to use tier 2 and no developing country was able to use tier 3 (Hardcastle and Baird, 2008;
10 Romijn et al., 2012) found more recently that only four tropical countries had a very small capacity
11 gap regarding the monitoring of their forests through inventories while the remaining 48 countries
12 had none to limited ability to undertake this monitoring process.

13 In order to overcome these gaps and uncertainties associated with lower tier approaches different
14 principles can be applied to form pools (Böttcher et al., 2008). For example, a higher level of
15 aggregation (i.e. in addition to a biomass pool include soil and litter, harvested products as part of
16 the MRV regime) decreases relative uncertainty as the losses in one pool (e.g. biomass) are offset by
17 gains in other pools (e.g. harvested products) (Böttcher et al., 2008). The exclusion of a pool (e.g.
18 soil) in an MRV regime should be allowed only if adequate documentation is provided that this
19 produces a conservative estimate (i.e. likely to be at least as high as the unknown actual values) of
20 emissions (Grassi et al., 2008). An international framework also needs to create incentives for
21 investments. In this respect, overcoming initialization costs and unequal access to monitoring
22 technologies is crucial for implementation of an integrated monitoring system, and fostering
23 international cooperation (Böttcher et al., 2009).

24 **2.4.4 Choice and design of policy instruments under uncertainty**

25 Whether motivated primarily by a binding multilateral climate treaty or by some other set of factors,
26 there is a growing set of policy instruments that countries have implemented or are considering for
27 dealing with climate change. We structure this subsection by considering two broad classes of
28 interventions for targeting the energy supply: interventions that focus on emissions, by placing a
29 market price or tax on CO₂ or other greenhouse gases; and interventions that promote research,
30 development, deployment, and diffusion (RDD&D) of particular technologies. In both types of
31 interventions, policy choices can be sensitive to uncertainties in technology costs, markets, and the
32 state of regulation in other jurisdictions and in the future. In the case of technology-oriented policy,
33 choices are also sensitive to the risks that particular technologies present. We then describe
34 instruments for fostering energy demand by focusing on lifestyle choice and energy efficient
35 products and technologies. Finally, we briefly contrast the effects of uncertainties in the realm of
36 climate adaptation with climate mitigation recognizing that more detail on the former can be found
37 in the report from Working Group II. At the outset we should note that few studies to date have
38 incorporated how System 1 behavior impacts on particular policy instruments, or on ways to
39 encourage System 2 behavior.

40 **2.4.4.1 Instruments creating market penalties for GHG emissions**

41 Market-based instruments place either a direct or opportunity cost on the emission of greenhouse
42 gases. This increases the cost of energy derived from fossil fuels, potentially leading firms involved in
43 the production and conversion of energy to invest in low carbon technologies. The actual investment
44 decision is affected by regulatory uncertainty with respect to whether a market instrument will be in
45 place in the future that creates an additional cost. There will also be regulatory uncertainty about
46 future carbon prices in the presence of a cap, given that a number of factors influence the
47 relationship between the size of the cap and the market price. These include fossil fuel prices,
48 consumer demand for energy, and economic growth more generally, each of which can lead to
49 volatility in carbon market prices (Alberola et al., 2008; Carraro and Favero, 2009; Chevallier, 2009).

1 Indeed, experience so far with the most developed carbon market—the European Emissions Trading
2 System (ETS)—reveals high volatility marked by not-infrequent collapses of the price to very low
3 values (Feng et al., 2011).

4 Numerous modelling studies have shown that regulatory uncertainty reduces the effectiveness of
5 market-based instruments, in terms of promoting investments into low-carbon technologies.
6 Assuming profit-maximizing firms, Yang et al., (2008) modelled optimal investment options under
7 conditions of uncertainty in the future carbon price, with the results being sensitive to assumptions
8 about relative technology prices. Blyth et al., (2007) modelled the behaviour of risk neutral profit
9 maximizers, and found that including uncertainty with respect to future policy causes carbon prices
10 to be between 16% and 37% higher than under conditions of policy certainty to achieve the same
11 patterns of investment. Fuss et al., (2009) used a real options model to show that increased
12 regulatory uncertainty leads to a slower pace of technological change, and higher cumulative
13 emissions for a given expected carbon price.

14 The effects of future regulatory changes are greater the more frequent those changes are even if the
15 policy changes are small. In other words, less frequent but larger policy changes have less of a
16 detrimental impact on overall emissions. Patiño-Echeverri et al., (2007) reached a similar conclusion
17 by examining the effects of uncertain carbon prices on the actions of a risk neutral investor and then
18 illustrated this effect by looking at decisions to invest in coal-fired power plants . Patiño-Echeverri et
19 al., (2009). Reinelt and Keith (2007) found that regulatory uncertainty increases social abatement
20 costs by as much as 50% by undertaking a similar analysis with respect to carbon capture and
21 storage (CCS). They found that the greater the flexibility, in terms of the availability of low cost
22 retrofit (adding CCS to an existing emissions source), the less the costs associated with uncertainty.
23 Zhao (2003) examines the effects of uncertainty in abatement cost on market based instruments
24 employing either a carbon tax or a tradable permit market. He finds that firms' investment
25 incentives into low carbon technology decreases with high uncertainty, but that the effect is greater
26 in the case of a tax than in the case of a tradable permit market.

27 The above studies considered the case of risk neutral investors. Fan et al., (2010) examined the
28 sensitivity of these results to increasing risk aversion, under two alternative carbon market designs:
29 one in which carbon allowances were auctioned by the government to firms, and a second in which
30 existing firms received free allowances due to a grandfathering rule. Under an auctioned system for
31 carbon allowances, the effect of risk aversion is to reduce the effect of regulatory uncertainty in
32 undermining the regime's effectiveness: increasing risk aversion leads to investments in low carbon
33 technologies. By contrast under a grandfathered market design, the effect of uncertainty is to push
34 investment behaviour close to what it would be in the absence of the carbon market: increasing risk
35 aversion leads to more coal investment. Fan et al., (2012) replicated these results using a broader
36 range of technological choices than in their paper. Fuss et al., (2012) used a very different modelling
37 methodology to reach similar conclusions by considering bio-energy producers in an auctioned
38 permit scheme.

39 One option to reduce carbon price volatility is to set a cap or floor for that price to stabilize
40 investment expectations (Jacoby and Ellerman, 2004; Philibert, 2009). Wood and Jotzo (2011) found
41 benefit of setting such a price floor , in terms of increasing the effectiveness of the carbon price at
42 stimulating investments, given a particular expectation of macroeconomic drivers (e.g., economic
43 growth, fossil fuel prices, all of which influence the degree to which a carbon cap is a constraint on
44 emissions). By contrast, Szolgayova et al., (2008) examined the effects of price cap using a real
45 options mode that specifically takes into account the value of waiting for more information before
46 committing to a particular decision. They found the cap stabilized expectations but in the process
47 lessened the effectiveness of an expected carbon price at altering investment behaviour. More
48 specifically investments into low carbon technologies are undertaken only because of the possibility
49 of very high carbon prices in the future. In another study based on the assumed presence of a
50 rational actor, Burtraw et al., (2010) find that a symmetric safety valve that sets both a floor and a

1 ceiling price outperforms a single sided safety valve in terms of both emissions reduction and
2 economic efficiency. Murray et al., (2009) suggest that a reserve allowance for permits outperforms
3 a simple safety valve in this regard.

4 Empirical research on the influence of uncertainty on carbon market performance has been
5 constrained by the small number of functioning markets making it difficult to infer effects from
6 differences in market design. The few studies to date suggest that the details of market design can
7 influence the perception of uncertainty, and in turn the performance of the market. More
8 specifically, investment behaviour into the Clean Development Mechanism (CDM) has been
9 influenced by uncertainties in terms of what types of projects are eligible (Castro and Michaelowa,
10 2011), and the actual number of Certified Emissions Reductions (CERs) that can be sold for a given
11 project (Richardson, 2008).

12 For the European Union's Emission Trading System (ETS), researchers have observed that expected
13 carbon prices do affect investment behaviour, but primarily for investments with very short
14 amortization periods. High uncertainty with respect to the longer-term market price of carbon has
15 limited the ETS effects on longer-term investments such as R&D or new power plant construction
16 (Hoffmann, 2007). Barbose et al. (2008) examined a region—the western United States—where no
17 ETS was functioning but many believed that it would and found that most utilities did consider the
18 possibility of carbon prices in the range of \$4 to \$22 a ton. At the same time, the researchers could
19 not determine whether the possibility of the carbon prices had an actual effect on their decisions,
20 because the researchers were unable to document the analysis the analysis underlying the utilities'
21 investment decisions, and thus whether the beliefs in the future carbon prices actually played a role.

22 ***2.4.4.2 Instruments promoting technological RDD&D***

23 Several researchers suggest that future pathways for RDD&D will be the determining factor for
24 emissions reductions (Prins and Rayner, 2007; Lilliestam et al., 2012). There are a number of
25 instruments that focus on this directly, by either supporting RDD&D with public funds or by
26 mandating particular technologies, rather than indirectly through a GHG or carbon penalty, which
27 provide an incentive but not a mandate to firms. Baker, Clarke and Shittu (2008) show that different
28 policy instruments may provide incentives for firms not just to invest in particular low carbon
29 technologies that already exist, but also to innovate new technologies that can be used later on. In
30 many cases, the instruments differ in terms of how they manage the risks that investors face, and
31 hence their relative effectiveness is quite sensitive to market uncertainties.

32 The literature already reviewed on market-based instruments shows high agreement that their
33 effectiveness at promoting RDD&D declines due to regulatory uncertainty, giving risk to policy
34 proposals to supplement a pure-market system with another instrument—such as a cap, floor, or
35 escape valve—to reduce price volatility and stabilize expectations. By contrast, combining a market-
36 based instrument with specific technology support can lead to greater volatility in the carbon price,
37 even when there is only very little uncertainty about which technologies will be assisted in the
38 coming years (Blyth et al., 2009).

39 Several empirical studies have compared the effectiveness of market instruments with other
40 instruments that provide direct stimulus to low carbon investments, at various stages in the RDD&D
41 chain. Looking early in the technology development process, Burer and Wüstenhagen (2009)
42 surveyed “greentech” venture capitalists in the United States and Europe using a stated preference
43 approach to identify which policy instrument or instruments would have the effect of reducing the
44 perceived risks of investment in a particular technology. They identified a strong preference on both
45 continents, but in particular Europe, for feed-in tariffs when compared with carbon markets and
46 renewable quota systems. These empirical findings are consistent with a behavioural model of firm
47 decision-making, in which perceived risks play a central role in determining choices. In the spirit of
48 System 1 behavior, venture capital investors typically look for short- to medium-term returns on

1 their investment, for which the presence of feed-in tariffs has the greatest positive effect. There is
2 no literature suggesting ways of shifting such decision-making towards the longer term.

3 The comparative effectiveness of feed-in tariffs in reducing perceived risk appears also to be present
4 later in the technology cycle during the project development stage. Butler and Neuhoff (2008), for
5 example, compared the feed-in tariff in Germany with the quota system in the United Kingdom, and
6 found the Germany system outperform the UK system on two dimensions, namely stimulating
7 overall investment quantity, and reducing costs to consumers. The primary driver was the
8 effectiveness of the feed-in tariff at reducing risks associated with future revenues from the project
9 investment, therefore making it possible to obtain project financing at a lower cost. Other
10 researchers replicate this finding using other case studies (Mitchell et al., 2006; Fouquet and
11 Johansson, 2008).

12 Even for a given technology support instrument, there are design choices that can affect investor
13 risks. Held et al. (2006) identified patterns of success across a wide variety of policy instruments in
14 Europe to stimulate investment in renewable energy technologies. They found that long-term
15 regulatory consistency was vital for new technology development in all cases. Lüthi and
16 Wüstenhagen (2011) surveyed investors with access to a number of markets, and found that they
17 steered their new projects to those markets with feed-in tariff systems as it was more likely than
18 other policy instruments to reduce their risks. Lüthi (2010) compared policy effectiveness across a
19 number of jurisdictions with feed-in tariffs, and found that above a certain level of return, risk-
20 related factors did more to influence investment than return-related factors.

21 There have been a number of empirical papers examining those risks and uncertainties that
22 investors perceive as most important. Leary and Esteban (2009) found efforts to stimulate the
23 development and deployment of wave and tide power to be hampered by regulatory uncertainty
24 with respect to coastal marine law as to where new developments could be sited. Komendantova et
25 al. (2012) examined perceptions among investors in solar projects in North Africa, and found
26 concerns about regulatory change and corruption to dominate concerns about terrorism and
27 technology risks. The same researchers modelled the sensitivity of required state subsidies for
28 project development in response to these risks, and found the subsidies required to stimulate a
29 given level of solar investment rose by a factor of three, suggesting large benefits to be associated
30 with efforts to stem corruption and stabilize regulations (Komendantova et al., 2011). Meijer et al.
31 (2007) examined the perceived risks for biogas project developers in the Netherlands, and found
32 technological, resource, and political uncertainty to be most important. In all of these examples, the
33 absence of historical data makes it is difficult to undertake a convincing *objective* assessment of the
34 actual risks facing investors. These studies are useful not because they confirm that investors are
35 behaving according to rational actor or behavioural models, but simply to document what are their
36 major subjective concerns. These findings give policy-makers the opportunity to address these
37 concerns.

38 Finally, policy discussions on particular technologies often revolve around the health and safety risks
39 associated with technology options, pathways, and systems such as nuclear energy (Pidgeon et al.,
40 2008; Whitfield et al., 2009), coal combustion (Carmichael et al., 2009; Hill et al., 2009) and
41 underground carbon storage (Itaoka et al., 2009; Shackley et al., 2009). There are also risks to
42 national energy security that have given rise to political discussions advocating the substitution of
43 domestically produced renewable energy for imported fossil fuels (Eaves and Eaves, 2007; Lilliestam
44 and Ellenbeck, 2011).

45 **2.4.4.3 Energy efficiency and behavioral change**

46 The reluctance of consumers to adopt energy efficient measures such as compact fluorescent bulbs,
47 energy efficient refrigerators, boilers and cooling systems as well as solar installations can be
48 attributed to misperceptions of their benefits in reduced energy costs coupled with an unwillingness
49 to incur the upfront costs of these measures---features of System 1 behavior.

1 Gardner and Stern (2008) identified a list of energy efficient measures that could reduce North
2 American consumers' energy consumption by almost 30% but found that individuals were not willing
3 to invest in them because they have misconceptions about their effectiveness Larrick and Soll (2008)
4 revealed that people in the U.S. mistakenly believe that gasoline consumption decreases linearly
5 rather than nonlinearly as an automobile's miles per gallon increases. Other studies show that the
6 general public has a poor understanding of the energy consumption associated with familiar
7 activities (Sterman and Sweeney, 2007). A national online survey of 505 participants by Attari et al.
8 (2010) revealed that most respondents felt that measures such as turning off the lights or driving
9 less were much more effective than energy efficient improvements in contrast to experts'
10 recommendations.

11 There are both behavioral and economic factors that can explain the reluctance of households to
12 incur the upfront costs of these measures. As the above studies indicate, individuals may
13 underestimate the savings in energy costs from investing in energy efficient measures. In addition
14 they are likely to have short time horizons and discount the future hyperbolically so that the upfront
15 cost is perceived to be greater than expected discounted reduction in energy costs. Coupled with
16 these forms of System 1 behaviour, households may have severe budget constraints that prohibit
17 them from investing in these energy efficient measures. If they intend to move in several years and
18 feel that the investment in the energy efficient measure will not be adequately reflected in an
19 increase in their property value, then it is economically rational for them not to invest in these
20 measures (Kunreuther et al.).

21 To encourage households to invest in energy efficient measures, programs need to be developed to
22 highlight the benefits from investing in the energy efficient measure in terms that the household can
23 understand and to spread the upfront costs over time so the measures are viewed as economically
24 viable and attractive. With respect to the first point, efforts are being designed to communicate
25 information on energy use and savings from investing in more efficient measures (Abrahamse et al.,
26 2005). The advent of the smart grid in Western countries, with its smart metering of household
27 energy consumption and the development of smart appliances will make it feasible to provide
28 appliance-specific feedback about energy use and energy savings to a significant number of
29 consumers within a few years. Developers of feedback interfaces of smart meters should be aware
30 of behavioural responses to such information and take some lessons from OPower, a company that
31 has been applying behavioural decision principles to the design of monthly bills, sent to residential
32 utility customers. Allcott (2011) showed that the provision of social norm information that
33 compared household energy use to those of neighbours succeeded in reducing energy consumption
34 by 2%, an effect equivalent to an electricity price increase of between 11 and 20%.

35 The PACE program in the United States directly addresses the second point. Under this program,
36 interested property owners opt-in to receive financing for improvements that is repaid through an
37 assessment on their property taxes for up to 20 years. PACE financing spreads the cost of energy
38 improvements such as weather sealing, energy efficient boilers and cooling systems, and solar
39 installations over the expected life of these measures and allows for the repayment obligation to
40 transfer automatically to the next property owner if the property is sold. PACE solves two key
41 barriers to increased adoption of energy efficiency and small-scale renewable energy: high upfront
42 costs and fear that project costs won't be recovered prior to a future sale of the property
43 (Kunreuther et al.).

44 **2.4.4.4 Adaptation and vulnerability reduction**

45 Compared to investment in mitigation, investments in adaptation appear to be more sensitive to
46 uncertainties in the local impacts and damage costs of climate change. This is unsurprising, for two
47 reasons. First, while both mitigation and adaptation may result in lower local damage costs
48 associated with climate impacts, in the case of adaptation the benefits flow directly from the action
49 taken (Prato, 2008), whereas for mitigation they are uncertain, given that they are contingent on the

1 mitigation decisions of people in other places and in the future (Webster et al., 2003). Second,
2 politically negotiated mitigation targets, such as the 2°C threshold, appear to be primarily
3 determined by what is feasible and affordable in terms of the pace of technological diffusion, rather
4 than by an optimization of mitigation costs and benefits (Hasselmann et al., 2003; Baker et al., 2008;
5 Hasselmann and Barker, 2008). Adaptation decisions, by contrast, may face fewer political and
6 technical constraints, and hence can more closely track what it needed in order to minimize
7 expected costs (Patt et al., 2007, 2009).

8 There are two main exceptions to this, in which case decisions on adaptation policies and actions
9 may be largely insensitive to uncertainties in climate. The first exception is where adaptation is
10 constrained by the availability of finance, such as international development assistance. Studies by
11 the World Bank, OECD, and other international organizations have estimated the financing needs for
12 adaptation in developing countries to be far larger than funds currently available (Agrawala and
13 Fankhauser, 2008; World Bank, 2010; Patt et al., 2010). In this case, adaptation actions become
14 sensitive to higher-level decisions concerning the allocation of available finance across competing
15 regions, a calculus that may depend on perceptions of relative vulnerability of people and
16 organizations, rather than the attributed local impacts of climate change (Klein et al., 2007; Hulme et
17 al., 2011). Funding decisions and political constraints at the national level can also constrain
18 adaptation to an extent that choices no longer are sensitive to uncertainties with respects to local
19 impacts (Dessai and Hulme, 2004, 2007).

20 The second main exception is where adaptation is severely constrained by a lack of local knowledge
21 and analytic skill, restrictions on what actions can be taken and/or cultural norms (Brooks et al.,
22 2005; Füssel and Klein, 2006; O'Brien, 2009; Jones and Boyd, 2011). Adaptive capacity could be
23 improved through investments in education, development of local financial institutes and property
24 rights systems, women's rights, and other broad-based forms of poverty alleviation. There is a
25 growing literature to suggest that such policies bring substantial benefits in the face of climate
26 change. These benefits that are relatively insensitive to the precise nature and extent of local
27 climate impacts (Folke et al., 2002; World Bank, 2010; Polasky et al., 2011). Such strategies are not
28 designed to make people resilient to particular climate risks, but rather to reduce their vulnerability
29 to a wide range of potential risks (Thornton et al., 2008; Eakin and Patt, 2011).

30 **2.4.5 Public support and opposition under uncertainty**

31 Climate policy, while designed to minimize the risks associated with climate change itself, necessarily
32 imply interventions into society that may carry negative effects at a number of different levels. At
33 the national or regional scale, one of the possible negative impacts is diminished competitiveness for
34 job creation. At the local level, negative effects can include adverse environmental impacts
35 associated with particular kinds of energy infrastructure and higher local prices of energy. Individuals
36 may feel that climate policies should be pursued, but at the same time may be concerned with short-
37 run costs they will incur. In this sub-section, we review what is known about public support or
38 opposition to climate policy in general, i.e. the goals, objectives, and instruments that public actors
39 adopt, before turning to support and opposition to discrete infrastructure projects. Finally, we
40 consider cross cutting issues associated with the science that is used to support or oppose specific
41 policy proposals. Across all three areas, there are strong ties to the behavioural factors influencing
42 System 1 thinking described in Section 2.2.

43 **2.4.5.1 Popular support for climate policy**

44 There is substantial evidence that people's support or opposition to proposed climate policy
45 measures is determined primarily by emotional factors and their past experience rather than
46 explicit calculations as to whether the personal benefits outweigh the personal costs. A national
47 survey in the United States found that people's support for climate policy also depended on cultural
48 factors, with regionally differentiated worldviews playing an important role (Leiserowitz, 2006), as

1 did a cross national comparison of Britain and the United States (Lorenzoni and Pidgeon, 2006), and
2 studies comparing developing with developed countries (Vignola et al., 2012).

3 One of the major determinants of popular support for climate policy is whether people have an
4 underlying belief that climate change is dangerous. This concern can be influenced by both cultural
5 facts and the methods of communication (Smith, 2005; Pidgeon and Fischhoff, 2011). Leiserowitz
6 (2005) found a great deal of heterogeneity linked to cultural effects with respect to the perception
7 of climate change in the United States. The use of language used to describe climate change—such
8 as the distinction between “climate change” and “global warming”— play a role in influencing
9 perceptions of risk, as well as considerations of immediate and local impacts (Lorenzoni et al., 2006).
10 The portrayal of uncertainties and disagreements with respect to climate impacts was found to have
11 a weak effect on whether people perceived the impacts as serious, but a strong effect on whether
12 they felt that the impacts deserved policy intervention (Patt, 2007).

13 An important question related to climate change communication is whether the popular reporting of
14 climate change through disaster scenarios has the effect of energizing people to support aggressive
15 policy intervention, or to become dismissive of the problem. A study examining responses to
16 fictionalized disaster scenarios found them to have differential effects on perceptions and support
17 for policy, reducing people’s expectation of the local impacts, while increasing their support for
18 global intervention (Lowe et al., 2006). Other studies found interactive effects: those who had low
19 awareness of climate change became concerned by being exposed to disaster scenarios, while those
20 with high awareness were dismissive of the possible impacts (Schiermeier, 2004).

21 Finally, the extent to which people believe it is possible to actually influence the future appears to be
22 a major determinant of their support for both individual and collective action to respond to climate
23 change. In the case of local climate adaptation, psychological variables associated with self-
24 empowerment were found to have played a much larger role in influencing individual behavior than
25 variables associated with economic and financial ability (Grothmann and Patt, 2005; Grothmann and
26 Reusswig, 2006). With respect to mitigation policy, perceptions concerning the barriers to effective
27 mitigation—belief that it was possible to respond to climate change—were found to be important
28 determinants of popular support (Lorenzoni et al., 2007).

29 ***2.4.5.2 Local support and opposition to infrastructure projects***

30 The issue of local support or opposition to infrastructure projects to implement climate policy is
31 related to the role that perceived technological risks play in the process. This has been especially
32 important with respect to nuclear energy, but is of increasing concern for carbon storage and
33 renewable energy projects.

34 In the case of renewable energy technologies, a number of factors appear to influence the level of
35 public support or opposition, factors that align well with a behavioral model in which emotional
36 responses are highly contextual. One such factor is the relationship between project developers and
37 local residents. Musall and Kuik (2011) compared two wind projects, where residents feared
38 negative visual impacts. They found that the fear was less, and the public support for the projects
39 higher when there was co-ownership of the development by the local community. A second factor is
40 the degree of transparency surrounding project development. Dowd et al. (2011) investigated
41 perceived risks associated with geothermal projects in Australia. Using a survey instrument, they
42 found that early, transparent communication of geothermal technology and risks tended to increase
43 levels of public support. A third such factor is the perception of economic costs and benefits that go
44 hand in hand with the perceived environmental risks. Zoellner et al. (2008) examined public
45 acceptance of three renewable technologies (grid-connected PV, biomass, and wind). They found
46 that perceived economic risks—in terms of higher energy prices—were the largest predictor of
47 acceptance. Concerns over local environmental impacts, including visual impacts, were of concern
48 where the perceived economic risks were high.

1 There have been many studies both assessing the risks and examining local support for carbon
2 capture and storage (CCS). According to Ha-Duong et al. (1997), the health and safety risks
3 associated with carbon capture and transportation technologies differ across causal pathways but
4 are similar in magnitude to technologies currently supported by the fossil-fuel industry. The safety of
5 the underground storage of CO₂ is a different concern, and has received attention in part for social
6 and economic reasons. If storage under the land were prohibited, then the industry would have to
7 turn to the more expensive option of storing under the sea floor. Using natural analogues, Roberts et
8 al. (2011) found that the health risks of natural CO₂ seeps in Italy were "significantly lower than
9 many socially accepted risks," that is three orders of magnitude lower than the probability of being
10 struck by lightning.

11 Despite these risk assessments, there is mixed evidence of public acceptance about CO₂ storage
12 because of safety concerns. For example, a storage research project was authorized in Lacq, France,
13 but another was halted in Barendreich, The Netherlands due to public opposition. No research has
14 been undertaken to date that identifies the drivers of public concern or acceptance, as well as the
15 anticipated risk levels associated with CO₂ storage.

16 Van Alphen et al. (2007) evaluated the concerns with CCS among important stakeholders, including
17 government, industry, and NGO representatives. They found support if the facility had a low
18 probability of leakage and was viewed a temporary measure. Wallquist et al. (2012) used conjoint
19 analysis to interpret a Swiss survey on the acceptability of CCS and found that concerns over local
20 risks and impacts—NIMBY concerns—dominated the fears over the long-term climate impacts of
21 leakage. The NIMBY concerns were less severe, and the public acceptance higher, for CCS projects
22 combined with biomass combustion, suggesting that positive feelings about removing CO₂ from the
23 atmosphere influences perceptions of local risks.

24 In the period between the Fourth Assessment Report and the accident at the Fukushima power plant
25 in Japan in March 2011, the riskiness of nuclear power as a climate mitigation option has received
26 increasing attention. Socolow and Glaser (2009) highlight the urgency of taking steps to reduce these
27 risks, primarily by ensuring that nuclear fuels and waste materials are not used for weapons
28 production. A number of papers examine the perceived risks of nuclear power among the public. In
29 the United States, Whitfield et al. (2009) found risk perceptions to be fairly stable over time with
30 expressing confidence in "traditional values" perceiving nuclear power to be less risky. In the United
31 Kingdom, Pidgeon et al. (2008) found a willingness to accept the risks of nuclear power when it was
32 framed as a means of reducing the risks of climate change, but that this willingness largely dissipated
33 when nuclear power was suggested as an alternative to renewable energy to accomplish this same
34 objective. Heal and Kunreuther (2010) focused on whether the risks associated with this technology
35 could be managed more efficiently by private insurance markets rather than through government
36 arrangements such as the Price-Anderson Act in the United States which imposes significantly
37 liabilities on the Federal Government should there be a catastrophic accident.

38 **2.4.5.3 Uncertainty and the science policy interface**

39 The linear model of linking science to policy, aptly described by the phrase "speaking truth to
40 power" (Price, 1965), presumes that scientific facts can be produced independently of social and
41 political considerations and can serve as unproblematic inputs to policy. This model implies that
42 public refusal to accept a firm scientific consensus must be the result of efforts by political interests
43 to undermine the truth. Thus, public opposition to the IPCC consensus on anthropogenic climate
44 change has been attributed to doubt raised by biased, industry-sponsored scientists with little
45 regard for the truth (Oreskes and Conway, 2010) .

46 Research on the relationship between science and policy, however, rejects the linear model as
47 simplistic, concluding that it does not adequately account for the complexity of science-based
48 policymaking (Jasanoff, 1990; Pielke, 2007; Shackley et al., 2009). Linking science to policy is better
49 understood as a recursive activity, involving analysis as well as deliberation (Stern and Fineberg,

1996) so as to bridge uncertainties, accommodate multiple viewpoints, and establish trust across heterogeneous communities. Accordingly, attention has increasingly focused on the role of institutions and policy practices in translating science to policy in ways that advance the public good.

To understand the nature of such translation, the concept of uncertainty needs to be examined more closely. Analysts have called attention to several different forms of uncertainty affecting the science-policy relationship. These can be summarized as follows:

- **Paradigmatic uncertainty.** This results from the absence of prior agreement on the framing of problems, on methods for scientifically investigating them, and on how to combine knowledge from disparate research traditions. Such uncertainties are especially common in cross-disciplinary, application-oriented research and assessment for meeting policy objectives (Gibbons, 1994; Nowotny et al., 2001).
- **Epistemic uncertainty.** This results from lack of adequate knowledge to characterize the nature and probability of outcomes. Stirling (2007) further distinguishes between uncertainty (insufficient knowledge to assess probabilities), ambiguity (insufficient knowledge about possible outcomes), and ignorance (insufficient knowledge of likely outcomes and their probabilities). Others have noted that producing more knowledge may exacerbate uncertainty, especially when actors disagree about how to frame a problem for scientific investigation (Beck, 1992; Gross, 2010).
- **Translational uncertainty.** This results from scientific findings that are incomplete or conflicting, so that they can be invoked to support divergent policy positions (Sarewitz, 2010). In such circumstances, protracted controversy often occurs as each side challenges the methodological foundations of the other's claims in a process called "experimenters' regress" (Collins, 1985).

Institutions that link science to policy must grapple with all of the above forms of uncertainty, often simultaneously. Because their work cuts across conventional lines between science and politics, these institutions have been called "boundary organizations" (Guston, 2001) and their function has been termed "hybrid management" (Miller, 2001). Straddling multiple worlds, science-policy institutions are required to meet both scientific and political standards of accountability. Whereas achieving scientific consensus frequently calls for bounding and closing down disagreements, achieving political legitimacy requires opening up areas of conflict in order to give voice to divergent perspectives.

The task of resolving conflicts in policy-relevant science is generally entrusted to multidisciplinary expert bodies. These organizations are best suited to addressing the paradigmatic uncertainties that arise when problems are novel or when synthesis is required across fields with different standards of good scientific practice. Bridging epistemic and translational uncertainties, however, imposes added demands. For expert advisory bodies to be viewed as legitimate they must represent all relevant viewpoints in a politically acceptable manner (Jasanoff, 1990, 2005a). What counts as acceptable varies to some degree across national decision-making cultures, each of which place different weights on experts' personal integrity, the reliability of their disciplinary judgments, and their ability to forge agreement across competing values (Jasanoff, 2005b, pp. 209–224).

To achieve legitimacy, institutions charged with linking science to policy must also open themselves up to public input at one or more stages in their deliberations. This process of "extended peer review" (Funtowicz and Ravetz, 1992) is regarded as necessary for the production of "socially robust knowledge," i.e., knowledge that can withstand public scrutiny and scepticism (Gibbons, 1994). Procedures that are sufficient to produce public trust in one political context may not work in others because national political cultures are characterized by different "civic epistemologies," i.e., culturally specific modes of generating and publicly testing policy-relevant knowledge (Jasanoff, 2005a).

1 International and global scientific assessment bodies confront additional problems of legitimacy
2 because they operate outside long-established national decision-making cultures and are
3 accountable to publics subscribing to different civic epistemologies (Jasanoff, 2010). The temptation
4 for such bodies has been to seek refuge in the linear model in the hope that the strength of their
5 internal scientific consensus will be sufficient to win wide political buy-in. The recent research on
6 linking science to policy suggests otherwise.

7 **2.5 Future research directions**

8 **[Authors note: to be discussed after examining comments on the FOD]**

9 **2.6 Frequently asked questions**

10 **[Note from the TSU: section to be done for the Second Order Draft]**

11

1 Appendix: Metrics of uncertainty and risk

2 A unified approach for all three WGs

3 The goal of any IPCC report is to inform the decision-making process in the context of climate
4 change, its impacts, and response strategies. Different disciplines contribute to this task, each
5 shaped by different historically grown standards and procedures of approval of scientific findings.
6 Since all these methodologically diverse disciplines are supposed to interactively contribute to
7 answering pertinent overarching questions, the IPCC has used “calibrated language” to characterize
8 the scientific understanding and associated uncertainties underlying assessment findings (Moss and
9 Schneider, 2000). In fact in AR4, all three Working Groups employed calibrated uncertainty language
10 for the first time (Mastrandrea et al., 2011) but used different metrics. For example, Working Group
11 III used only qualitative summary terms.

12 In preparation for AR5, an IPCC Cross-Working Group meeting on Consistent Treatment of
13 Uncertainties took place in July 2010. Following this meeting, a writing team, including a Co-Chair
14 and LAs from each IPCC Working Group (including an LA of this Chapter), scientists from the
15 Technical Support Units, and other experts in treatment of uncertainties drafted the Guidance Note
16 (“GN”) for Lead Authors of the IPCC Fifth Assessment Report on Consistent Treatment of
17 Uncertainties (Mastrandrea et al., 2010). This Appendix present key elements of the GN and
18 interpret them to frame the handling of uncertainty and risk in a consistent manner throughout the
19 AR5-WGIII.

20 Key concepts

21 The GN recommends organizing the reporting of certainty and/or uncertainty with respect to so-
22 called key findings (to be defined below) using the categories evidence, agreement, confidence,
23 probability and traceable account.

24 A key finding is a “conclusion of the assessment process that the author team may choose to include
25 in the chapter’s Executive Summary...” (M11)

26 “Types of evidence include, for example, mechanistic or process understanding, underlying theory,
27 model results, observational and experimental data, and formally elicited expert judgment. The
28 amount of evidence available can range from small to large, and that evidence can vary in quality.
29 Evidence can also vary in its consistency, i.e., the extent to which it supports single or competing
30 explanations of the same phenomena, or the extent to which projected future outcomes are similar
31 or divergent.

32 The degree of agreement is a measure of the consensus across the scientific community on a given
33 topic and not just across an author team. It indicates, for example, the degree to which a finding
34 follows from established, competing, or speculative scientific explanations. Agreement is not
35 equivalent to consistency. Whether or not consistent evidence corresponds to a high degree of
36 agreement is determined by other aspects of evidence such as its amount and quality; evidence can
37 be consistent yet low in quality.” (M11)

38 The GN further introduces the central concept of confidence as a subjective function of evidence and
39 agreement. “A level of confidence provides a qualitative synthesis of an author team’s judgment
40 about the validity of a finding; it integrates the evaluation of evidence and agreement in one
41 metric.” (M11) Hence, “confidence” expresses the extent as to which the IPCC authors do in fact
42 support a key finding. If confidence was “large enough” (to be detailed below), the GN suggests
43 further specification of key findings in probabilistic terms²

² Hereby a reader of the GN should not be confused by the fact that whenever the GN employ the term
“likelihood” they refer to what statisticians do call “probability.” Quite the contrary, in no instance does the

1 Ebi (2011) (and in a similar vein also Jones (2011)) suggests that “theory” be treated as a third,
2 independent, input for “confidence.” When there are insufficient confidence levels (given a certain
3 decision problem at stake), the reader would systematically receive more detailed information as to
4 why there was insufficient data. Case where there theory and empirical data can support a
5 confidence level needs to be distinguished from situations where this is not the case. We regard the
6 GN mapping to be logically consistent with Ebi’s model. Authors always have the freedom to provide
7 more information than requested by the GN, in the form of a traceable account (see § below).

8 To conclude the list of categories “the author team’s evaluation of evidence and agreement provides
9 the basis for any key findings it develops and also the foundation for determining the author team’s
10 degree of certainty in those findings. The description of the author team’s evaluation of evidence
11 and agreement is called a traceable account in the GN. Each key finding presented in a chapter’s
12 Executive Summary will include reference to the chapter section containing the traceable account
13 for the finding.” (M11)

14 **General recommendations of the GN**

15 Before elaborating on a sequence of practical recommendations with respect to the reporting of
16 cases of increasing precision, the GN provides a list of the following items:

- 17 • There is a fundamental and delicate trade-off between generality and precision of a statement
18 the authors should keep in mind: “It is important for author teams to develop findings that are
19 general enough to reflect the underlying evidence but not so general that they lose substantive
20 meaning.”
- 21 • The GN also elucidates on the treatment of causal chains: “For findings (effects) that are
22 conditional on other findings (causes), consider independently evaluating the degrees of
23 certainty in both causes and effects, with the understanding that the degree of certainty in the
24 causes may be low. In particular, this approach may be appropriate for high-consequence
25 conditional outcomes.” For example, authors should be aware that composite probabilities in a
26 causal chain are by definition lower than individual probabilities.
- 27 • “Findings can be constructed from the perspective of minimizing false positive (Type I) or false
28 negative (Type II) errors, with resultant tradeoffs in the information emphasized.”
- 29 • The GN recommends taking more of a risk-management perspective than in AR4. “Sound
30 decision making that anticipates, prepares for, and responds to climate change depends on
31 information about the full range of possible consequences and associated probabilities. Such
32 decisions often include a risk management perspective. Because risk is a function of probability
33 and consequence, information on the tails of the distribution of outcomes can be especially
34 important. Low-probability outcomes can have significant impacts, particularly when
35 characterized by large magnitude, long persistence, broad prevalence, and/or irreversibility.
36 Author teams are therefore encouraged to provide information on the tails of distributions of
37 key variables, reporting quantitative estimates when possible and supplying qualitative
38 assessments and evaluations when appropriate.”
- 39 • The treatment of uncertainty is discussed GN1-5:
 - 40 • GN1: “At an early stage, consider approaches to communicating the degree of certainty in
41 key findings in your chapter using the calibrated language described below. Determine the
42 areas in your chapter where a range of views may need to be described, and those where
43 the author team may need to develop a finding representing a collective view. Agree on a

GN’s use of “likelihood” refer to the “likelihood function” being derived from “probability conditioned on alternative parameter values” as a statistician would understand it.

1 moderated and balanced process for doing this in advance of confronting these issues in a
2 specific context.”

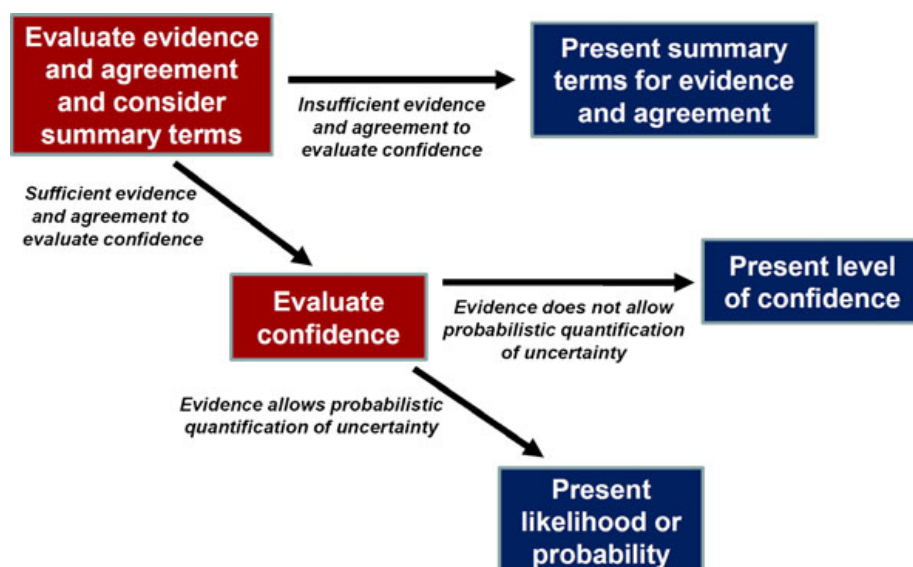
- 3 • GN2: “Be prepared to make expert judgments in developing key findings, and to explain
4 those judgments by providing a traceable account: a description in the chapter text of your
5 evaluation of the type, amount, quality, and consistency of evidence and the degree of
6 agreement, which together form the basis for a given key finding. Such a description may
7 include standards of evidence applied, approaches to combining or reconciling multiple lines
8 of evidence, conditional assumptions, and explanation of critical factors. When appropriate,
9 consider using formal elicitation methods to organize and quantify these judgments (Morgan
10 et al., 2009).
- 11 • GN3: “Be aware of a tendency for a group to converge on an expressed view and become
12 overconfident in it (Morgan and Henrion, 1990). Views and estimates can also become
13 anchored on previous versions or values to a greater extent than is justified. One possible
14 way to avoid this would be to ask each member of the author team to write down his or her
15 individual assessments of the level of uncertainty before entering into a group discussion. If
16 this is not done before group discussion, important views may be inadequately discussed
17 and assessed ranges of uncertainty may be overly narrow (Straus et al., 2009). Recognize
18 when individual views are adjusting as a result of group interactions and allow adequate
19 time for such changes in viewpoint to be reviewed.” In fact, Morgan (2011) suggests that
20 “once they have read the relevant literature, but before they begin discussions to reach a
21 group consensus, each member of an authoring team could be asked to engage in an expert
22 elicitation about the value of a few key coefficients. The range of results could then serve as
23 an input to inform the process of developing a group consensus judgment.”
- 24 • GN4: “Be aware that the way in which a statement is framed will have an effect on how it is
25 interpreted (e.g., a 10% chance of dying is interpreted more negatively than a 90% chance of
26 surviving; (Kahneman and Tversky, 1979). Consider reciprocal statements to avoid value-
27 laden interpretations (e.g., report chances both of dying and of surviving).”
- 28 • GN5: “Consider that, in some cases, it may be appropriate to describe findings for which
29 evidence and understanding are overwhelming as statements of fact without using
30 uncertainty qualifiers.”
- 31 • The review procedure is covered by GN6 and GN7:
 - 32 • GN6: “Consider all plausible sources of uncertainty. Experts tend to underestimate structural
33 uncertainty arising from incomplete understanding of or competing conceptual frameworks
34 for relevant systems and processes (Morgan et al., 2009). Consider previous estimates of
35 ranges, distributions, or other measures of uncertainty, their evolution, and the extent to
36 which they cover all plausible sources of uncertainty.”
 - 37 • GN7: “Assess issues of uncertainty and risk to the extent possible. When appropriate
38 probabilistic information is available, consider ranges of outcomes and their associated
39 probabilities with attention to outcomes of potential high consequence...” (Lempert et al.,
40 2003).

41 Building on these more general statements, the GN then defines a sequence of steps for determining
42 the degree of certainty in a specific finding. M11 further spells out the recommendations as follows:

43 “The first step in this process (the upper left of Fig. 3) is for the author team to consider the
44 appropriate summary terms corresponding to its evaluation of evidence and agreement. As outlined
45 in GN8 and depicted in Fig. 3, the summary terms for evidence (characterizing the type, amount,
46 quality, and consistency of evidence) are limited, medium, or robust. The GN indicates that evidence

1 is generally most robust when there are multiple, consistent independent lines of high-quality
 2 evidence. The summary terms for the degree of agreement are low, medium, or high.”

3



4

5 **Figure 2.3** Process for evaluating and communicating the degree of certainty in key findings.

6 As the second step in determining the degree of certainty in a key finding, the author team decides
 7 whether there is sufficient evidence and agreement to evaluate confidence. This task is relatively
 8 simple when evidence is robust and/or agreement is high. For other combinations of evidence and
 9 agreement, the author team should evaluate confidence whenever possible. For example, even if
 10 evidence is limited, it may be possible to evaluate confidence if agreement is high. Evidence and
 11 agreement may not be sufficient to evaluate confidence in all cases, particularly when evidence is
 12 limited and agreement is low. In such cases, the author team instead presents the assigned summary
 13 terms as part of the key finding. The qualifiers used to express a level of confidence are very low,
 14 low, medium, high, and very high. Figure 4 depicts summary statements for evidence and agreement
 15 and their flexible relationship to confidence.” (M11)

16 The GN deliberately abstains from defining the functional mapping from evidence and agreement on
 17 confidence, as this represents a highly complex process that may vary from case to case. Instead
 18 authors are encouraged to justify their mapping as part of the traceable account. The GN point out
 19 that normally, findings of (very) low confidence shall not be reported, except for “areas of major
 20 concern”, if carefully explained. This again points to an elevated risk perspective in the GN.

21 The nine possible combinations of summary terms for evidence and agreement are shown in Figure
 22 3 along with their relationship to the confidence scale. Confidence generally increases towards the
 23 top-right corner as suggested by the increasing strength of shading. By construction, confidence
 24 increases when there is higher agreement and more robust evidence.

	High agreement Limited evidence	High agreement Medium evidence	High agreement Robust evidence
	Medium agreement Limited evidence	Medium agreement Medium evidence	Medium agreement Robust evidence
	Low agreement Limited evidence	Low agreement Medium evidence	Low agreement Robust evidence

Figure 2.4 A depiction of evidence and agreement statements and their relationship to confidence. Figure reproduced and legend adapted from the GN.

To communicate probability or likelihood, the GN encourages one to use the following coarse-graining “calibrated language” that is empirically supported as noted by (Morgan, 2011):

GN10: “Likelihood... provides calibrated language for describing quantified uncertainty. It can be used to express a probabilistic estimate of the occurrence of a single event or of an outcome [...]. Likelihood may be based on statistical or modeling analyses, elicitation of expert views, or other quantitative analyses. The categories defined in this table can be considered to have “fuzzy” boundaries. A statement that an outcome is “likely” means that the probability of this outcome can range from $\geq 66\%$ (fuzzy boundaries implied) to 100% probability. This implies that all alternative outcomes are “unlikely” (0-33% probability). [...]”

The GN notes that authors should report a certain category of precision only if the requirements for lower categories are fulfilled as well. Overly precise statements on probability are meaningless if they cannot be justified on the basis of underlying processes. Each category of precision is illustrated by an example within the context of WGIII.

GN11: “Characterize key findings regarding a variable...using calibrated uncertainty language that conveys the most information to the reader, based on the criteria (A-F) below (Kandlikar et al., 2005). These criteria provide guidance for selecting among different alternatives for presenting uncertainty, recognizing that in all cases it is important to include a traceable account of relevant evidence and agreement in your chapter text.

Category A: *A variable is ambiguous, or the processes determining it are poorly known or not amenable to measurement:*

Confidence should not be assigned; assign summary terms³ for evidence and agreement [...]. Explain the governing factors, key indicators, and relationships. If a variable could be either positive or negative, describe the pre-conditions or evidence for each.”

Example: Within certain time windows it was not clear whether prices for photovoltaic showed a continued negative trend or whether the trend was reversed in response to feed-in tariffs in some European countries.

Category B: *“The sign of a variable can be identified but the magnitude is poorly known:*

Assign confidence when possible; otherwise assign summary terms for evidence and agreement [...]. Explain the basis for this confidence evaluation and the extent to which opposite changes would not be expected.”

³ A summary term is of one of the qualitative scales (*Agreement* or *Evidence*) in Fig. 2.4

1 *Example:* Most experts would agree that the global adaptive capacity for the shift in rainfall patterns
2 is positive. But the magnitude might be difficult to determine without more explicit models from the
3 field of development economics.

4 **Category C:** *“An order of magnitude can be given for a variable:*

5 Assign confidence when possible; otherwise assign summary terms for evidence and agreement [...].
6 Explain the basis for estimates and confidence evaluations made, and indicate any assumptions. If
7 the evaluation is particularly sensitive to specific assumptions, then also evaluate confidence in
8 those assumptions.”

9 *Example:* Many WGIII authors may conclude that the order of magnitude of global mitigation costs is
10 known as a function of a prespecified target. However, if all social frictions (in a society “not yet
11 prepared to mitigate”) were taken into account, costs might be considerably higher.

12 **Category D:** *“A range can be given for a variable, based on quantitative analysis or expert judgment:*

13 Assign likelihood or probability for that range when possible; otherwise only assign confidence [...].
14 Explain the basis for the range given, noting factors that determine the outer bounds. State any
15 assumptions made and estimate the role of structural uncertainties. Report likelihood or probability
16 for values or changes outside the range, if appropriate.”

17 *Example:* Based on a comparison of models, intervals on mitigation costs under first-best conditions
18 can be given.

19 **Category E:** *“A likelihood or probability can be determined for a variable, for the occurrence of an
20 event, or for a range of outcomes (e.g., based on multiple observations, model ensemble runs, or
21 expert judgment):*

22 Assign a likelihood for the event or outcomes, for which confidence should be “high” or “very high”
23 [...]. In this case, the level of confidence need not be explicitly stated. State any assumptions made
24 and estimate the role of structural uncertainties. Consider characterizing the likelihood or
25 probability of other events or outcomes within the full set of alternatives, including those at the
26 tails.”

27 *Example:* See example below in F.

28 **Category F:** *“A probability distribution or a set of distributions can be determined for the variable
29 either through statistical analysis or through use of a formal quantitative survey of expert views:*

30 Present the probability distribution(s) graphically and/or provide a range of percentiles of the
31 distribution(s), for which confidence should be “high” or “very high” (see Paragraphs 8-10). In this
32 case, the level of confidence need not be explicitly stated. Explain the method used to produce the
33 probability distribution(s) and any assumptions made, and estimate the role of structural
34 uncertainties. Provide quantification of the tails of the distribution(s) to the extent possible.”

35 Difference between E and F: Category F in its pure form requires a probability measure for the entire
36 domain of a variable. Category E requires less information than F, as certain quantiles are sufficient.
37 Nevertheless, for both categories, one may require a set (consisting of more than one element) of
38 probability measures rather than a single one.

39 *Example:* Experience curves have been evaluated using econometric methods to derive probabilistic
40 statements with respect to learning curve coefficients.

41 The GN concludes:

42 **“In summary, communicate uncertainty carefully, using calibrated language for key findings, and
43 provide traceable accounts describing your evaluations of evidence and agreement in your
44 chapter.”**

1 Category F in its pure form fits the requirements of the “standard decision model” in the “tools”
2 section. For all other cases, workarounds need to be defined if the uncertainties reported were to be
3 put in a decision context. Non-probabilistic criteria like dominance, minimax, min-regret and others
4 should be considered, but might not utilize all the information content provided by the data.
5 Defining decision criteria that fulfill desirable axioms such as time consistency is a field of active
6 research.

7 **WGIII perspective:**

8 A major part of AR5-WGIII will report on scenarios characterized by epistemic uncertainties with
9 respect to some parameters and the structure of the model. In evaluating a mitigation policy it will
10 be important first to separate the effects induced by different normative and other “external”
11 scenario assumptions before model results are pooled.

12 In view of the requirements of the certainty assessment sequence specified in GN11, a hindcasting
13 approach may not be feasible so that probabilistic statements may be the exception rather than the
14 rule. To date, our understanding of the relationship between a macroeconomic model and ‘reality’
15 has not been characterized by a formal relationship that enables one to specify error terms but by
16 more informal models. M11 also notes that it is often not clear what facts should be used to
17 calibrate the model and advocates experiments to compare models. This may increase our
18 understanding of the underlying philosophies in model construction so one can undertake
19 hindcasting experiments in the future.

20 As hindcasting is of central importance in the other WGs, we encourage WGIII-authors to motivate
21 the basis of their modeling approaches (e.g. axiomatic, qualitative historical-empirical based) so that
22 one can determine when hindcasting can be undertaken. This will enhance a mutual understanding
23 of approaches and the meaning of the reported results across WGs.

24

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