PART 1. SOURCES AND TYPES OF UNCERTAINTY[11]

There are a number of things about climate change, and its likely consequences, that are unique. However, uncertainty, even irreducible uncertainty, is not one of them. Uncertainty is ubiquitous in virtually all fields of science and human endeavor. As Benjamin Franklin wrote in 1789 in a letter to Jean-Baptiste Leroy, "In this world nothing is certain but death and taxes." And, even in those cases, the timing and nature of the events are often uncertain.

Sometimes uncertainty can be reduced through research, but there are many settings in which one simply cannot resolve all-important uncertainties before decisions must be made. In our private lives, we choose where to go to college, what career to pursue, what job to take, whom to marry, whether and when to have children, all in the face of irreducible uncertainty. Similarly, corporations and governments regularly choose what policies to adopt, and where to invest resources, in the face of large and irreducible uncertainty.

By far the most widely used formal language of uncertainty is probability[12]. Many of the ideas and much of the vocabulary of probability were first developed in a "frequentist" framework to describe the properties of random processes, such as games of chance, which can be repeated many times. In this case, assuming that the process of interest is stable over time, or "stationary," probability is the value to which the event frequency converges in the long run as the number of

[11] Portions of the discussion in this section draw heavily on ideas and language from Morgan and Henrion (1990).
[12] There are a few alternative "languages" that have been advanced to describe and deal with uncertainty. These are briefly discussed in Section 2.

trials increases. Thus, in this frequentist or classical framework, probability is a property of a theoretically infinite series of trials, rather than of a single event.

While today some people stick to a strict classical interpretation of probability, many statisticians, as well as many of the experimental scientists we know, often adopt a "personalist", "subjectivist" or "Bayesian" view. In many settings, this has the consequence that probability can be used as a statement of a person's degree of belief given all available evidence. In this formulation, probability is not only a function of an event, but also of the state of information i that is available to the person making the assessment. That is, the probability, P, of event X is represented as $P\,(X|i)$ where the notation "$|i$", reads "conditional on i". Thus, $P\,(X|i)$ means the probability given that all the information is available to the person making the judgment at the same time when the value of the probability P is made. In this framework, obviously a person's value of P may change as more or different information, i, becomes available.

In a personalist or Bayesian framework, it is perfectly appropriate to say, based on a subjective interpretation of polling data, results from focus group discussions, and ones own reading of the political climate, "I think there is an 80% chance that Jones will win the next congressional election in this district." However, because it involves the outcome of a single unique future event, such a statement has no meaning in a frequentist framework.

In the face of large amounts of data on a repeating event, and a belief that the process being considered is stationary, the subjectivist probability should reduce to the same value as the classical probability. Thus, for example, if you need to estimate the probability that the midmorning high speed Shinkansen train from Kyoto will arrive on time in Tokyo on a Tuesday morning next month, and you have access to a data set of all previous arrival times of that train, you would probably want to simply adopt the histogram of those times as your probability distribution on arrival time.

Suppose, however, that you want to estimate how long it takes to complete the weekly shopping for a family of four in your community. If you happen to be the person doing the shopping for a family of four on a regular basis in that community, then, as in the case with the Shinkansen, you will have hundreds of observations to rely on in estimating a probability distribution. The large amount of data available to you helps you understand that the answer has features that depend on the time of day, day of the week, special occasions, and so on. If you do not shop that often, your ability to estimate time for shopping will be less informed and more likely to be in error.

Does a subjectivist view mean that one's probability can be completely arbitrary? "No," Morgan and Henrion (1990) answer "…because if they are legitimate probabilities, they must be consistent with the axioms of probability." For example, if you assign probability *p* that an event *X* will occur, you should assign 1-*p* to its complement, that *X* doesn't occur. The probability that one of a set of mutually exclusive events occurs should be the sum or their probabilities. In fact, subjective probabilities should obey the same axioms as objective or frequentist probabilities, otherwise they are not probabilities…"

Subjective probabilities are intended to characterize the full spectrum of degrees of belief one might hold about uncertain propositions. However, there exists a long-standing debate as to whether this representation is sufficient. Some judgments may be characterized by a degree of ambiguity or imprecision distinct from estimates of their probability. Writing about financial matters, Knight (1921) contrasted risk with uncertainty, using the first term to refer to random processes whose statistics were well known and the latter term to describe unknown factors poorly described by quantifiable probabilities. Ellsberg (1961) emphasized the importance of this difference in his famous paradox, where subjects are asked to play a game of chance in which they do not know the probabilities underlying the outcomes of the game[13]. Ellsberg found that many subjects make choices that are inconsistent with any single estimate of probabilities, which nonetheless reflect judgments about which outcomes can be known with the most confidence.

Guidance developed by Moss and Schneider (2000) for the IPCC on dealing with uncertainty describes two key attributes that they argue are important in any judgment about climate change: the amount of evidence available to support the judgment being made and the degree of consensus within the scientific community about that judgment. Thus, they argue, judgments can be sorted into four broad types as shown in Figure 1.1. Many decisions involving climate change entail judgments in all four quadrants of this diagram.

Subjective probabilities seem clearly appropriate for addressing the established cases across the top of this matrix. There is more debate about the most appropriate methods for dealing with the others. A variety of approaches exist, such as belief functions, certainty factors, second order

[13]Specifically consider two urns each with 100 balls. In urn 1, the color ratio of red and blue balls is not specified. Urn 2 has 50 red and 50 blue balls. If asked to bet on the color of a ball drawn from one of these urns most people do not care if the ball is drawn from urn 1 or 2 and give a probability to either color of 0.5. However, when asked to choose an urn when betting on a specified color most people prefer urn 2. The first outcome implies $p(r_1)=p(r_2)=p(b_1)=p(b_2)$, while the second, it is argued, implies $p(r_1)<p(r_2)$ and $p(b_1)<p(b_2)$. Ellsberg and others discuss this outcome as an illustration of an aversion to ambiguity.

probabilities, and fuzzy sets and fuzzy logic, that attempt to quantify the degree of belief in a set of subjective probability judgments[14]. Each of these approaches provides an alternative calculus that relaxes the axioms of probability. In particular, they try to capture the idea that one can gain or lose confidence in one of a mutually exclusive set of events without necessarily gaining or losing confidence in the other events. For instance, a jury in a court of law might hear evidence that makes them doubt the defendant's alibi without necessarily causing them to have more confidence in the prosecution's case.

A number of researchers have applied these alternative formulations to the challenge of characterizing climate change uncertainty and there is no final consensus on the best approach. However, so long as one carefully specifies the question to be addressed, our judgment is that all four boxes in Figure 1.1 can be appropriately handled through the use of subjective probability, allowing a wide range or a multiple set of plausible distributions to represent the high levels of uncertainty, and retaining the axioms of probability. As Smithson (1988) explains:

> "One of the most frequently invoked motivations for formalisms such as possibility and Shaferian belief theory is that one number is insufficient to represent subjective belief, particularly in the face of what some writers call "ignorance"…Probabilist reply that we need not invent a new theory to handle uncertainty about probabilities. Instead we may use meta-probabilities [such as second order probability]. Even such apparently non-probabilistic concepts as possibility can be so represented…One merely induces a second-order probability distribution over the first-order subjective probabilities."

When the subjective probabilistic judgments are to be used in decision making, we believe, as outlined in Section 7, that the key issue is to employ decision criteria, such as robustness, that are appropriate to the high levels of uncertainty.

[14]For reviews of these alternative formulations see Smithson (1988) and Henrion (1999).

Much of the literature divides uncertainty into two broad categories, termed opaquely (for those of us who are not Latin scholars), aleatory uncertainty and epistemic uncertainty. As Paté-Cornell (1996) explains, aleatory uncertainty stems "…from variability in known (or observable) populations and, therefore, represents randomness" while epistemic uncertainty "…comes from basic lack of knowledge about fundamental phenomena (…also known in the literature as ambiguity)"[15].

While this distinction is common in much of the more theoretical literature, we believe that it is of limited utility in the context of climate and many other applied problems in assessment and decision making where most key uncertainties involve a combination of the two.
A far more useful categorization for our purposes is the split between "uncertainty about the value of empirical quantities" and "uncertainty about model functional form." The first of these may be either aleatory (the top wind speed that occurred in any Atlantic hurricane in the year 1995) or epistemic (the average global radiative forcing produced by anthropogenic aerosols at the top of the atmosphere during 1995). There is some disagreement within the community of experts on whether it is even appropriate to use the terms epistemic or aleatory when referring to a model.

Empirical quantities represent properties of the real world, which, at least in principle, can be measured. They include"…quantities in the domains of natural science and engineering, such as the oxidation rate of atmospheric pollutants, the thermal efficiency of a power plant, the failure rate of a valve, or the carcinogenic potency of a chemical, and quantities in the domain of the

[15]The Random House Dictionary defines *aleatory* as "of or pertaining to accidental causes; of luck or chance; unpredictable" and defines *epistemic* as "of or pertaining to knowledge or the conditions for acquiring it."

social sciences, such as demand elasticity's or prices in economics, or judgmental biases in psychology. To be empirical variables must be measurable, at least in principle, either now or at some time in the future.

These should be sufficiently well specified so that they can pass the clarity test. Thus it is permissible to express uncertainty about an empirical quantity in the form of a probability distribution. Indeed, we suggest that the only types of quantity whose uncertainty may appropriately be represented in probabilistic terms are empirical quantities[16]. This is because they are the only type of quantity that is both uncertain and can be said to have a true, as opposed to an appropriate or good value"[17].

Uncertainty about the value of an empirical quantity can arise from a variety of sources: these include lack of data; inadequate or incomplete measurement; statistical variation arising from measurement instruments and methods; systematic error and the subjective judgments needed to estimate its nature and magnitude; and inherent randomness. Uncertainty about the value of empirical quantities can also arise from sources such as the imprecise use of language in describing the quantity of interest and disagreement among different experts about how to interpret available evidence.

Not all quantities are empirical. Moreover, quantities with the same name may be empirical in some contexts and not in others. For example, quantities which represent a decision maker's own

[16]This advice is not shared by all authors. For example, Cyert and DeGroot (1987) have treated uncertainty about a decision maker's own value parameters as uncertain. But, see our discussion about in the next paragraph.

[17]Text in quotation marks in this and the preceding paragraph come directly from the writings of two of the authors, Morgan and Henrion (1990).

value choice or preference, such as a discount rate, coefficient of risk aversion, or the investment rate to prevent mortality ("value of life") represent choices about what he or she considers to be appropriate or good. If decision makers are uncertain about what value to adopt, they should perform parametric or "switchover" analysis to explore the implications of alternative choices[18]. However, if an analyst is modeling the behavior of *other* decision makers, and needs to know how they will make such choices, then these same quantities become empirical and can appropriately be represented by a probability distribution[19].

Some authors refer to some forms of aleatory uncertainty as "variability." There are cases in which the distinction between uncertainty about the value of an empirical quantity and variability in that value (across space, time or other relevant dimensions) is important. However, in many practical analyses, maintaining a distinction between uncertainty and variability is not especially important (Morgan and Henrion, 1990) and maintaining it can give rise to overly complicated and confusing analysis. Some people who accept only a frequentist notion of probability, insist on maintaining the distinction because variability can often be described in terms of histograms or probability distributions based only on a frequentist interpretation.

A model is a simplified approximation of some underlying causal structure. Debates, such as whether a dose-response function is really linear, and whether or not it has a threshold below

[18]In this example, a parametric analysis might ask, "what are the implications of taking the value of life to be 0.5, or 1 or 5, or 10 or 50-million dollars per death averted?" A "switchover" analysis would turn things around and ask "at what value of life" does the conclusion I read switch from Policy A to Policy B?" If the policy choice does not depend upon the choice of value across the range of interest, it may not be necessary to further refine the value.

[19]For a more detailed discussion of this and similar distinctions see the discussion in Section 4.3 of Morgan and Henrion (1990).

which no health effect occurs, are not really about what model is "true". None of these models is a complete, accurate representation of reality. The question is what is a more "useful" representation given available scientific knowledge and data and the intended use that is to be made of, or decisions to be based on, the analysis. In this sense, uncertainty about model functional form is neither aleatory nor epistemic. The choice of model is part pragmatic. Good (1962) described such a choice of model as "type II rationality" - how can we choose a model that is a reasonable compromise between the credibility of results and the effort to create and analyze the model (collect data, estimate model parameters, apply expert judgment, compute the results, *etc.*).

Uncertainty about model functional form can arise from many of the same sources as uncertainty about the value of empirical quantities: inadequate or incomplete measurements and data which prevent the elimination of plausible alternatives; systematic errors which mislead folks in their interpretation of underlying mechanisms; inadequate imagination and inventiveness in suggesting or inferring the models which could produce the available data; and disagreement among different experts about how to interpret available evidence.

In most of the discussion that follows, by "model functional form" we will mean a description of how the world works. However, when one includes policy-analytic activities, models may also refer to considerations such as decision makers' "objectives" and the "decision rules" that they apply. These are, of course, normative choices which a decision maker or analyst must make. A fundamental problem, and potential source of uncertainty on the part of users of such analysis, is that the people who perform such analysis are often not explicit about the objectives and decision rules they are using. Indeed, sometimes they skip (unknowingly and inconsistently) from one to another decision rule in the course of doing an analysis.

All of the preceding discussion has focused on factors and processes that we know or believe exist, but, about which our knowledge is in some way incomplete. In any field as climate change and its impacts, there are also things about which we are completely ignorant. While Donald Rumsfeld (2002) was widely lampooned in the popular press, he was absolutely correct when he noted that "…there are known unknowns. That is to say, we know there are some things we do not know. But there are also unknown unknowns, the ones we don't know we don't know."

Things we know we do not know can often be addressed and sometimes understood through research. Things about which we do not even recognize we don't know, are only revealed by adopting an always-questioning attitude toward evidence. This is often easier said than done. Recognizing the inconsistencies in available evidence can be difficult, since as Thomas Kuhn (1962) has noted we interpret the world through mental models or "paradigms" that may make it difficult to recognize and pursue important inconstancies. Weick and Sutcliffe (2001) observe that "A recurring source of misperception lies in the temptation to normalize an unexpected event in order to preserve the original expectation. The tendency to normalize is part of a larger tendency to seek confirmation for our expectations and avoid disconfirmations. This pattern ignores vast amounts of data, many of which suggest that trouble is incubating and escalating." Weick and Sutcliffe (2001)

Freelance environmental journalist Dianne Dumanoski (1999) captured this issue well when she noted:

> Scientific ignorance sometimes brings many surprises. Many of the big issues we have reported on involve scientist quibbling about small degrees of uncertainty. For example, at the beginning of the debate on ozone depletion, there were arguments about whether the level or erosion of the ozone layer would be 7% or 13% within 100 years. Yet in 1985, a report came out from the British Antarctic survey, saying there was something upwards to a 50% loss of ozone over Antarctica. This went far beyond any scientist's worst-case scenario. Such a large loss had never been a consideration on anyone's radar screen and it certainly changed the level of the debate once it was discovered. Uncertainty cuts both ways. In some cases, something that was considered a serious problem can turn out to be less of a threat. In other cases, something is considered less serious than it should be and we get surprised…

Perhaps the ever folksy but profound Mark Twain[20] put it best when he noted "It ain't what you don't know that gets you in trouble. It's what you know for sure that just ain't so."

[20] <www.quotedb.com/quotes/1097>.

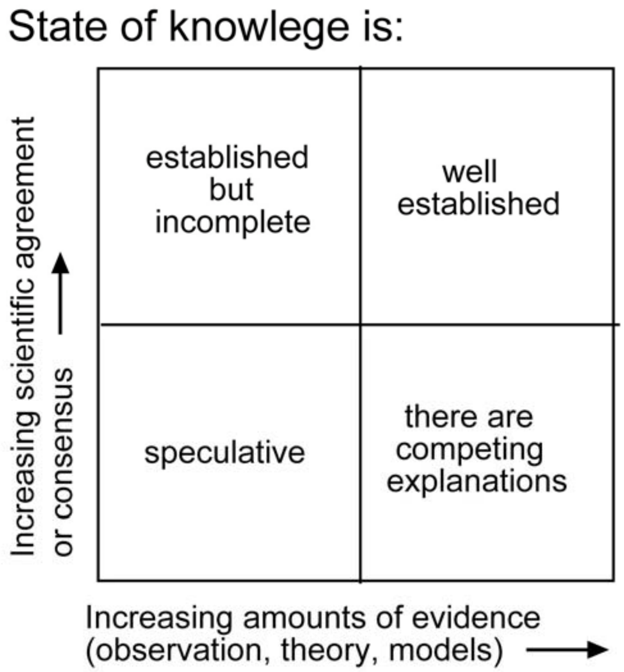

Figure 1.1 Categorization of the various states of knowledge that may apply in different aspects of climate and related problems. Redrawn from Moss and Schneider (2000).

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