Science AAAS

Visualizing Uncertainty About the Future

David Spiegelhalter, *et al.*

Science **333**, 1393 (2011);
DOI: 10.1126/science.1191181

Visualizing Uncertainty About the Future

David Spiegelhalter,[1]* Mike Pearson,[1] Ian Short[2]

We are all faced with uncertainty about the future, but we can get the measure of some uncertainties in terms of probabilities. Probabilities are notoriously difficult to communicate effectively to lay audiences, and in this review we examine current practice for communicating uncertainties visually, using examples drawn from sport, weather, climate, health, economics, and politics. Despite the burgeoning interest in infographics, there is limited experimental evidence on how different types of visualizations are processed and understood, although the effectiveness of some graphics clearly depends on the relative numeracy of an audience. Fortunately, it is increasingly easy to present data in the form of interactive visualizations and in multiple types of representation that can be adjusted to user needs and capabilities. Nonetheless, communicating deeper uncertainties resulting from incomplete or disputed knowledge—or from essential indeterminacy about the future—remains a challenge.

Faced with uncertainty about the future, people largely rely on their gut feelings to make decisions (*1*) influenced by past experiences, affect and emotion, the views of acquaintances, and cultural beliefs (*2*). For millennia, these intuitive responses have served us well, but there are situations in which a more analytic approach is likely to offer greater precision and deeper insight. For example, an individual may be faced with a financial decision with uncertain returns, or may need to choose between alternative medical treatments, or even appraise the odds being offered when gambling. An organization may need to decide whether to take precautions against bad weather ruining an event. Policy-makers may wish to assess the benefits of a public health intervention or the potential impact of a hazard on the natural environment.

In a more analytic approach to such situations, a general feeling of uncertainty about the future is replaced by two components: a list of possible outcomes and an assessment of their probabilities. Such assessments can be made on the basis of judgments or assumptions embodied in statistical models, which inevitably introduces a subjective element. Some argue that "probability does not exist" (*3*); our view is that probabilities are best treated as reasonable betting odds constructed from available knowledge and information.

Explanation of uncertainty presents a serious challenge, particularly to an audience with a wide range of scientific and mathematical expertise. In this article we examine the success of graphic visualizations for communicating probabilities to a wider public, and we draw inspiration from the strong tradition of using graphics to represent the frequency of events. For example, after the Crimean War, Florence Nightingale created diagrams resembling roses (*4*) (Fig. 1) to illustrate that far more soldiers died from preventable diseases than directly from wounds. These powerful images had a major impact in Nightingale's campaign to improve sanitary conditions in army hospitals. Seventy years later, the Austrian philosopher and economist Otto Neurath developed a picture "language" he called Isotype (*5*) as an educational tool in prewar socialist Vienna, which was used, for example, to describe the employment of women (Fig. 2). In contrast to the subjective influences acting in probability assessments, these compelling graphics depicted objective facts about the world.

We recognize three key concepts in evaluating techniques for displaying probabilistic predictions: (i) heuristics ("common sense") and accompanying biases applied in the face of uncertainty (*6*); (ii) risk perception and the role of factors such as personality and numeracy (*7*, *8*); and (iii) the type of graphic presentation of data being used—whether static images or interactive software (*9*). We focus on broad forms of visualization using a selection of examples, passing over details of graphic design and acknowledging that we only cover a small part of the whole communication process. Previous reviews (*8*–*15*) indicate there are few reproducible experimental findings for assessing best practice in visualizing uncertainty. Instead, reviewers have emphasized how graphics can be adapted to the aims of the communicator, stressing the importance of the context of the communica-

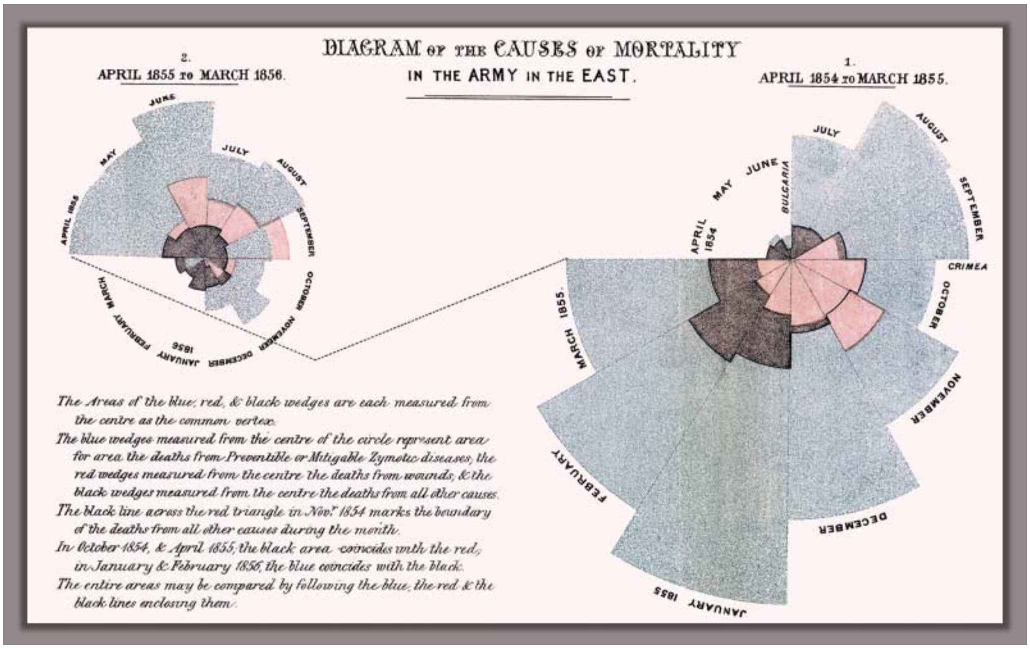

Fig. 1. Florence Nightingale's two rose-like graphs (*4*), each consisting of three overlaid polar area charts, representing deaths from sickness (blue), deaths from wounds (red), and deaths from other causes (black). Each sector corresponds to a month, and the area of a sector is proportional to the number of deaths per 1000 soldiers during that month. The drop in deaths from sickness followed the introduction of sanitary measures in early 1855.

[1]Centre for Mathematical Sciences, University of Cambridge, Cambridge CB3 0WB, UK. [2]Department of Mathematics and Statistics, The Open University, Milton Keynes MK7 6AA, UK.

*To whom correspondence should be addressed. E-mail: d.spiegelhalter@statslab.cam.ac.uk

tion exercise and the needs and capabilities of the audiences.

The main objective of a visualization may simply be to grab an audience's attention—a goal achieved by Nightingale with her flamboyant rose diagrams. Once we have the audience's attention, we may wish not only to inform audience members, but also to alter their feelings, change their behavior, or encourage them to weigh the possible benefits or harms of different actions (*13*). It may be important to communicate detailed numerical information or just convey the essence of a message. There may also be an ethical imperative to provide transparent information (*9*). When designing a communication, the desired outcome must be considered from the start; as Ancker *et al*. argue, "graphical features that improve accuracy of quantitative reasoning appear to be different from features that induce behavior change, and features that viewers like may not support either of the two goals" (*11*). Here, we assume that the mission is to inform rather than persuade (*9*).

We begin by briefly discussing the use of words and numbers in conveying probabilities, and then move on to consider visualization of uncertainty for subjects ranging from the fairly innocuous (results of football matches) to the personal (consequences of medical interventions) and then to the strongly disputed (future climate change). We consider static graphics of both discrete and continuous outcomes, as well as interactive web animations. Finally, we present a vision of future possibilities, illustrated with some of our own preliminary work, including techniques for portraying uncertainty about the probabilities themselves.

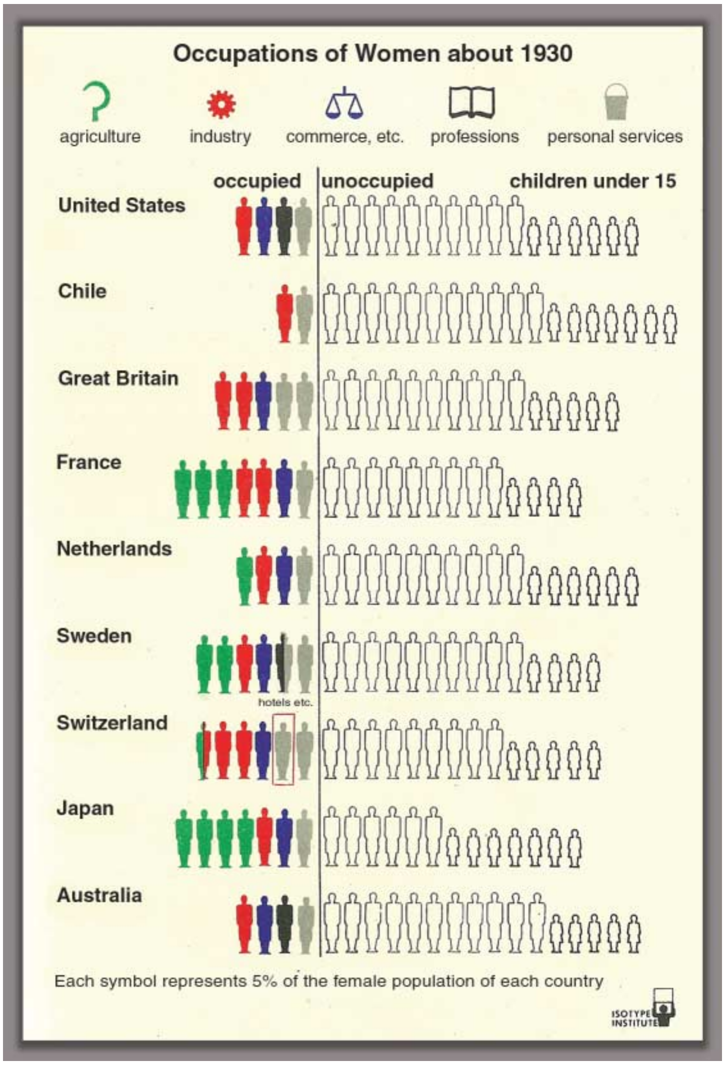

Fig. 2. Image from the Isotype Institute illustrating the proportions of women employed in different countries in 1930 and their occupations. [From (*63*)]

Communicating Uncertainty with Words and Numbers

Probabilities can be described fluidly with words, using language that appeals to people's intuition and emotions (*13*). But the attractive ambiguity of language becomes a failing when we wish to convey precise information, because words such as "doubtful," "probable," and "likely" are inconsistently interpreted (*16*). Further ambiguities in verbally communicating uncertainty can arise from language difficulties and literacy (*10*), although there have been attempts to impose consistency in the use of language. For example, the Intergovernmental Panel on Climate Change (IPCC) defined "very likely" in sentences such as "Most of the observed increase in global average temperatures since the mid-20th century is very likely due to the observed increase in anthropogenic greenhouse gas concentrations" to mean a 90 to 99% probability (*17*).

If we require precision, then numerical probabilities convey information succinctly and accurately, and are easily compared (*13*). A major difficulty in offering numerical probabilities, however, is that target audiences may have low numeracy. For example, in a recent population-based survey (*18*), the question "Which of the following numbers represents the biggest risk of getting a disease? 1 in 100, 1 in 1000, or 1 in 10?" was answered incorrectly by 25% of U.S. participants and 28% of German participants. Using odds or decimals as formats for numerical probability compounds such difficulties and adds to the problem of distinguishing absolute risks from relative risks. There are additional challenges in interpreting conditional probabilities, as highlighted, for example, in studies on the perception of biomedical screening test results (*19*).

Another crucial issue is the choice of perspective in presenting information, known as framing. For example, a recent poster campaign in the London Underground proclaimed that "99% of young people do not commit crimes" to create a deliberate positive focus on 99% of youth being law-abiding rather than the criminal 1%. Positive framing is also used for product promotion—for instance, when food is advertised "95% fat free"—to shift perception to belief that the food is healthy. Another example is provided by statistics for outcomes of cardiac surgery: In the United States, mortality rates are published, whereas the United Kingdom publishes survival rates, which provide a more favorable impression of outcomes (*20*). One tactic to avoid biases from framing is to use frequencies of the form "Out of 100 operations on people like you, we expect 95 to be successful and 5 to be unsuccessful," which attempts to avoid framing bias by describing both positive and negative outcomes. It also explicitly includes the reference class "100 operations on people like you" (*19*). In weather forecasts, inclusion of the reference class and framing are important issues. Consider the assertion "There is a 60% probability of precipitation tomorrow." The correct interpretation is that there will be rain in the specified place and time on 60% of days like tomorrow, based, for example, on rain predicted in 60% of computer simulations of weather forecasts. However, the statement is often misinterpreted to mean the percentage of time it will rain tomorrow, or the percentage of area on which it will rain (*21*). Such misperceptions result from confusion between probability and variability, and providing the reference class "days like tomorrow" can help understanding (*22*).

To convey uncertainty in simple terms, probabilities are often presented as fractions (such as 1/10) or natural frequencies (such as 1 in 10), but both these formats may lead to ratio bias or denominator neglect (*23*). Ratio bias is the tendency of probability perception to be influenced by the specific frequencies depicted (*24*), and in particular by the numerator, so that 1 in 20 may be perceived as being a smaller probability than 5 in 100 or 50 in 1000. In denominator neglect,

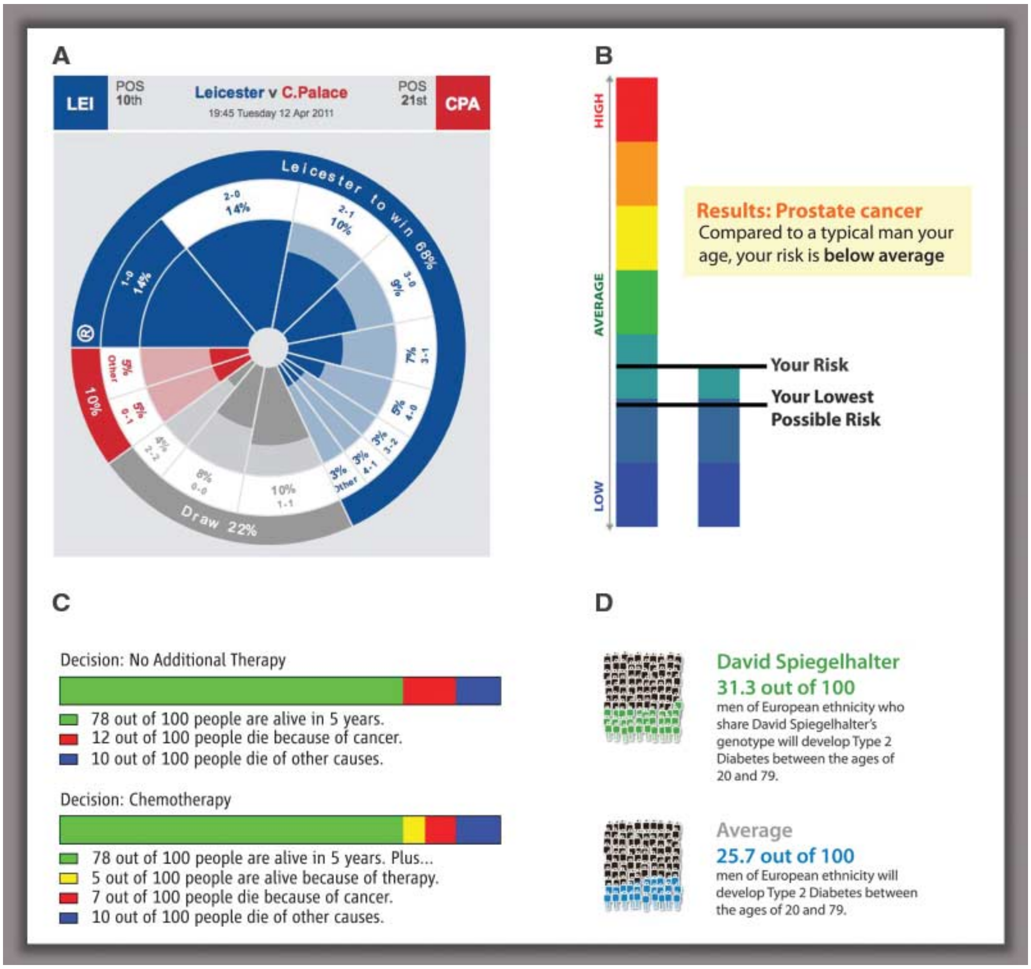

Fig. 3. Visualizations of probabilities for discrete events. (**A**) Pie chart displaying possible results of a U.K. football match (*64*) between Leicester and Crystal Palace, with Leicester the home team. The size of each slice, determined by its angle at the center, represents the probability of a particular final goal score; for example, the probability of Leicester scoring 1, Crystal Palace 0, is 14%: this is assessed to be the most likely outcome and so the outer white band is colored. This probability is also represented by the radius of the inner strongly colored "wedge" in each slice, which may give a misleading impression because, for instance, the wedge representing 14% (2-0) is substantially larger than the wedge representing 10% (2-1). In contrast, Florence Nightingale used area rather than radius to represent her data in creating the rose diagram in Fig. 1. (The score in the actual football match was 1-1.) (**B**) The right vertical bar chart represents David Spiegelhalter's risk of being diagnosed with prostate cancer, based on lifestyle information and the Harvard School of Public Health's disease risk web site, www.yourdiseaserisk.wustl.edu; the left vertical bar provides a qualitative scale (*65*). (**C**) A stacked horizontal bar chart from *Adjuvant! Online* (*66*) representing the benefits from adjuvant (labeled "additional") chemotherapy for a fictitious woman with colon cancer. A text description of the expected outcomes for 100 women with and without chemotherapy is also supplied. [© 2008 American Society of Clinical Oncology (*72*)] (**D**) Icon plot provided by 23andMe (*67*) for David Spiegelhalter's probability of developing type 2 diabetes between age 20 and age 79 based solely on specific genetic markers, relative to a standard population. In fact the subject has reached 58 without getting the disease. [Image © 2008–2011 23andMe, Inc. (*72*)]

attention is fixated on the number of events, without taking any account of the size of the population (*25*). If ratios are used, then it is important to use consistent denominators, and powers of 10 (such as "1 in 10"or "1 in 100") are easier to understand (*13*). Because of mixed experimental findings, the merits of using frequencies instead of percentages are contested (*7*, *10*, *26*, *27*).

Representing Probabilities with Graphics

A suitably chosen graphic can summarize data concisely, illuminate hidden patterns (*12*, *28*), gain and hold attention (*29*), enliven information, and inspire the viewer. Graphics can be tailored for the audience (*12*) and this can help people with low numeracy (*7*). On the other hand, graphics can arouse emotion (*2*), and overemphasis of negative consequences can lead to risk aversion (*15*) and higher perception of risks. In this section we focus on probabilities for discrete events that can be represented using standard graphical tools for conveying magnitude, such as pie charts, bar charts, and icon arrays (Fig. 3).

Pie charts are particularly useful for exhibiting single proportions (*9*) and are usually familiar and acceptable to a general public audience. They also provide a part-to-whole comparison because they represent all possible outcomes explicitly. Pie charts use area to represent probability, which can make comparisons between multiple charts difficult, although this can be aided by adding tick marks around the circumference (*12*). A novel display of the probabilities for different results of a U.K. football match is shown in Fig. 3A. Although we find this attractive, its complexity may cause confusion, and it has a potentially misleading feature (Fig. 3A, legend).

Bar charts are valuable for conveying magnitude and making comparisons (*13*). The chart in Fig. 3B, intended for a general audience, is simple and makes effective use of color but omits numeric values of risks (*30*). There is some reassurance in learning that your risk of prostate cancer is below average for your age, but there is no communication of the absolute risk. Furthermore, Fig. 3B exhibits negative framing, in that risks of cancer, rather than probabilities of not getting cancer, are displayed (*11*). In contrast, Fig. 3C compares alternative treatments numerically and gives complete part-to-whole information in describing all possible outcomes.

Bar charts (fig. S1) were also used by NASA's recent retrospective assessment of the risks of the Space Shuttle (*31*), which concluded that the risks had been substantially greater than assessed at the time—there was only a 6% probability of reaching the 25th launch (Challenger) without losing a craft. Their bar chart has mixed and rather confusing labeling of probabilities, including decimals, percentages, and odds.

Some studies suggest that a simple icon array can provide better understanding of disease risk than a bar chart (*32*). Icon arrays vividly display part-to-whole relationships and can counter denominator neglect, particularly in low-numeracy groups (*25*, *33*), as well as producing an affective response (*2*). Two sets of 100 equally sized human icons are shown in Fig. 3D, and those with diabetes are distinguished by color and grouped together. Icons representing a specific outcome can be scattered among the other icons (fig. S2). Although scattering better communicates unpredictability, it can be difficult to assess magnitudes and make comparisons, particularly for people with low numeracy (*34*).

Line graphs are generally well understood (*12*) and can be used to portray the way in which probabilities given to events can change over time. For example, fig. S3 shows the odds for Barack Obama winning the 2008 U.S. presidential election given in a betting exchange each day during the year preceding the election.

Natural frequencies appear to be superior to percentages in improving understanding of biomedical screening tests (*19*, *22*), owing to the cognitive effort required for interpreting conditional probabilities. Data from the U.K. Breast Cancer Screening Programme (*35*) are used in Fig. 4 to illustrate the outcomes of a mammography test on a population with a 1% prevalence of breast cancer. The test is positive for around 90% of women with cancer, but it is also positive for around 10% of women without cancer. The issue (*36*) is to communicate the probability that a woman who tests positive actually has breast cancer: The fact that this probability is only 8% is generally unintuitive. This is a notoriously tricky problem, but understanding can be greatly improved (*19*, *22*) by supplementing the icon array with a tree diagram. Audiences respond well to multiple types of display of the same information, and the composite diagram in Fig. 4 not only allows part-to-whole comparisons, but also shows how the probabilities are worked out.

Contrasting risks over different orders of magnitude presents a particular challenge to the choice of scale used in a diagram. A common solution is to use a logarithmic scale, ranging from, say, 1 in 10,000,000 to certainty, presented as a risk ladder (fig. S4A), or alternatively as a linear scale with a magnified portion for small risks (fig. S4B). Perception is strongly influenced by design of the scale (*11*), and perceived risk is often associated with position on the scale rather than the underlying magnitude. Hence, providing comparative information within a risk ladder can help understanding in low-numeracy groups (*37*).

Representing Uncertainty About Continuous Quantities

Uncertainty about a future continuous quantity, such as future temperature change or economic growth, is generally expressed as a full probability distribution derived from a mathematical model. This might be tabulated using summary statistics, such as its mean, median, variance, interquartile range, and so on, but greater impact in communicating uncertainty

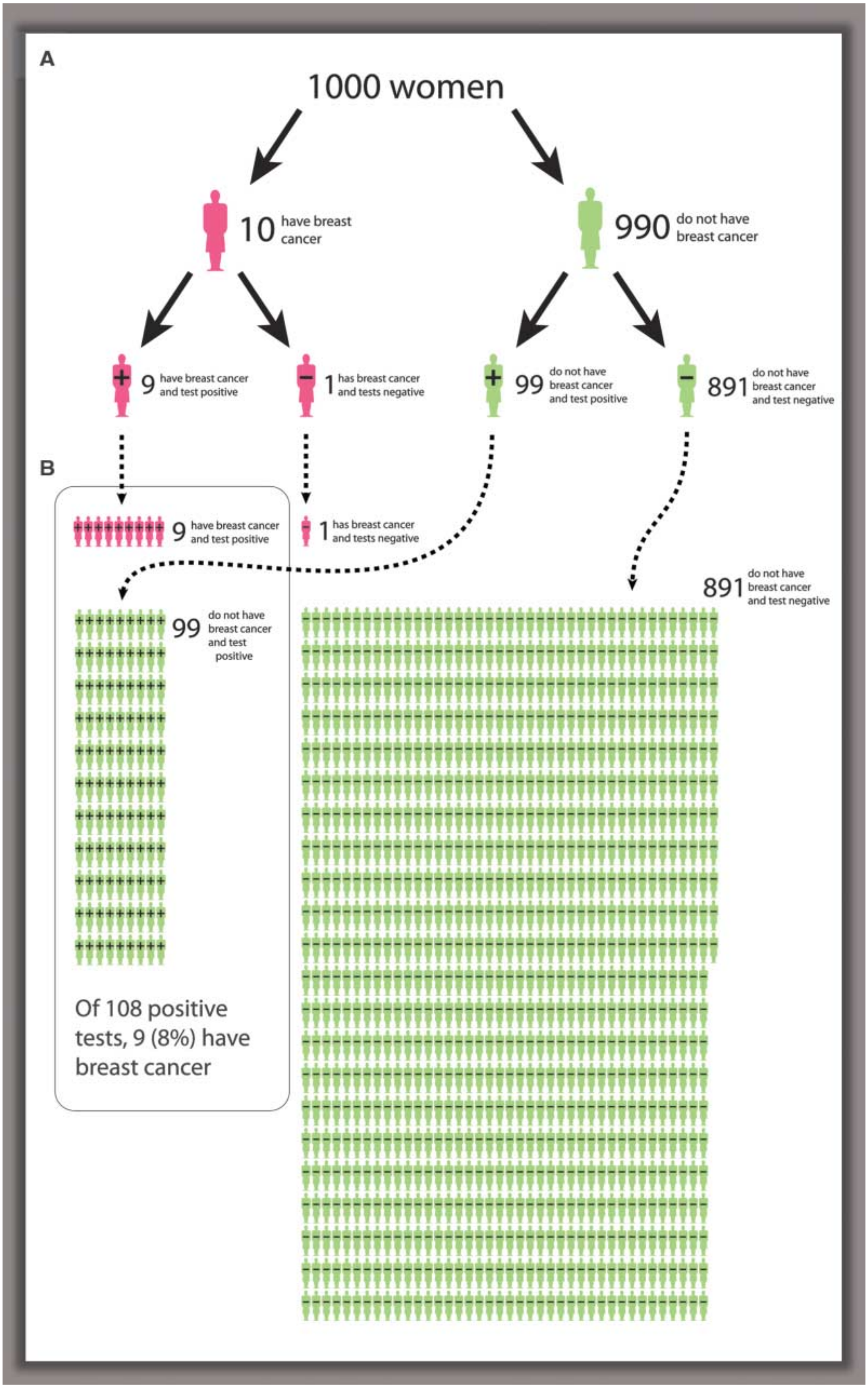

Fig. 4. Visualizations of the predictive accuracy of a screening test. (**A**) Tree diagram showing the consequences for 1000 women attending mammography screening from a population with 1% prevalence of the disease, when the screening test correctly classifies 90% of women with cancer and 90% of women without cancer. Although nearly all the women with cancer are detected, they are greatly outnumbered by false-positive tests arising from those without cancer. (**B**) Icon array of the same information, which shows explicitly that out of 108 positive tests, only 9 (8%) would be expected to reveal breast cancer.

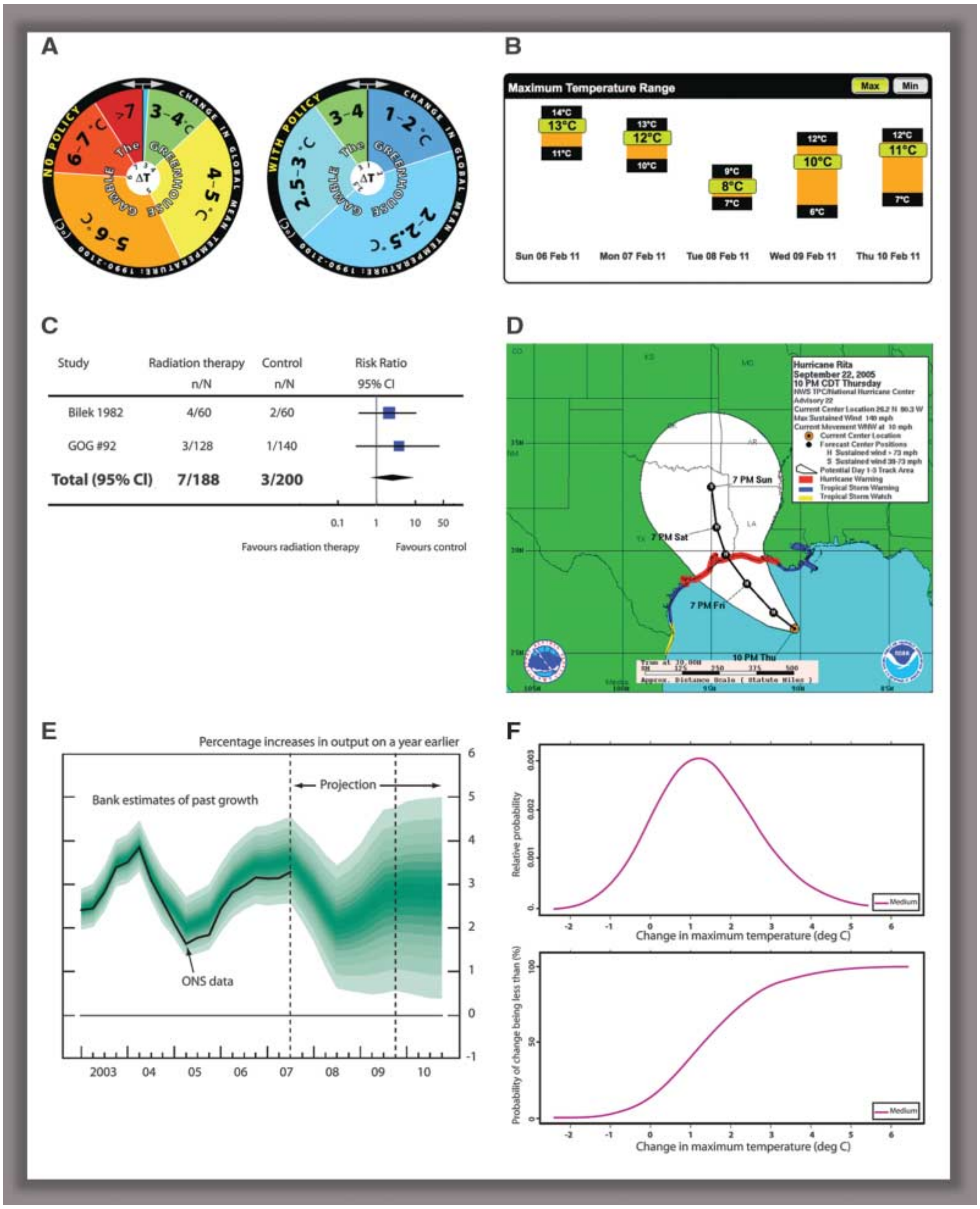

Fig. 5. Visualizations of probability distributions for continuous quantities. (**A**) "Roulette wheels" showing possible global temperature rises by 2100 under different policy scenarios (*68*). (**B**) 95% prediction intervals produced by the U.K. Meteorological Office for the maximum temperature expected for 5 days in Peterborough, U.K.; the central figure represents the most likely maximum temperature (*69*). (**C**) 95% uncertainty intervals obtained from the Cochrane Collaboration for the effect of adjuvant radiotherapy, after surgery for cancer of the cervix, on the incidence of hematological adverse events. There are two studies that together resulted in 7 of 188 adverse events in patients given radiation therapy, compared with 3 of 200 adverse events in control patients not given the treatment. The composite estimated risk ratio was 2.4, but with considerable uncertainty (*56*). The top right shows 95% uncertainty intervals represented by a horizontal line, with a square, whose size is proportional to the numbers of patients studied, drawing the eye to the more important central values of larger studies. In the row labeled Total, a diamond shape again deemphasizes the extremes values. Strictly speaking, this is not a visualization of future uncertainty. [Image © Cochrane Collaboration (*72*)] (**D**) "Cone of uncertainty" for hurricane path warnings in Florida. The central black line is the "most likely" path, and there is a two-thirds chance of the path being somewhere in the white region (*70*). (**E**) Fan chart for future economic growth in the U.K. as recorded in November 2007 by the Bank of England (*43*). The black line shows actual economic growth (according to current Office for National Statistics assessments) up to November 2007. Because these are provisional figures, there is still uncertainty as to the magnitude of past growth. (**F**) Probability distribution (top panel) and cumulative distribution (bottom panel) for change in maximum temperature between 2010 and 2020 under a medium-emission scenario for a 25-km^2 area in the U.K. containing the University of Cambridge (*71*). The probability distribution expresses considerable uncertainty around a "most likely" estimate of around 1°C, while the cumulative distribution makes it easier to read off, for example, a central 90% interval. [© 2009 Crown Copyright (*72*)]

to a general audience can be achieved by a visualization.

The roulette wheel in Fig. 3A is a static representation of a model created by researchers at MIT. This device was used in public presentations to illustrate the gamble we take on the environment if we fail to implement sufficient policies to tackle climate change (*38*). The image captures attention with an attractive layout and bright colors, although some effort is required to interpret the graphic, and the uncertainty associated with the probabilities is not shown.

Short-term weather predictions often come with quantifiable uncertainty. In Fig. 5B, predictions of maximum temperatures are displayed for five consecutive days. The best estimate is shown for each day, as well as high and low values, representing a 90% prediction interval. A potential problem is that these intervals may be wrongly interpreted as representing variability in temperature throughout the day. An additional disadvantage of this approach is that values within the interval appear equally likely, encouraging users to focus on the extremes of the interval, which are substantially less likely to occur than the best estimate. A similar issue arises with the use of error bars on graphs (*39*), but this can be countered. For example, Fig. 5C shows a "forest plot" of the type used extensively in the synthesis of medical evidence obtained from multiple clinical trials or epidemiological studies. The left side of a forest plot comprises a list of the studies included in the analysis, and the right side is a graphical depiction of the results together with a confidence measure (denoted by the length of the line) and a measure of the strength of the study (shown by the area of the squares). The total, or summarized, measure of the effect is represented by a diamond; the width of the diamond indicates the confidence interval, so if the wing of the diamond crosses the vertical line, which represents no effect, then the data are not statistically significant.

Uncertainty about where certain events might occur, such as the trajectory of a hurricane, can be represented on a map as a "cone of uncertainty" (Fig. 5D). Here the most likely path of a hurricane is indicated by a black line, and there is a two-thirds chance that the path will lie somewhere in

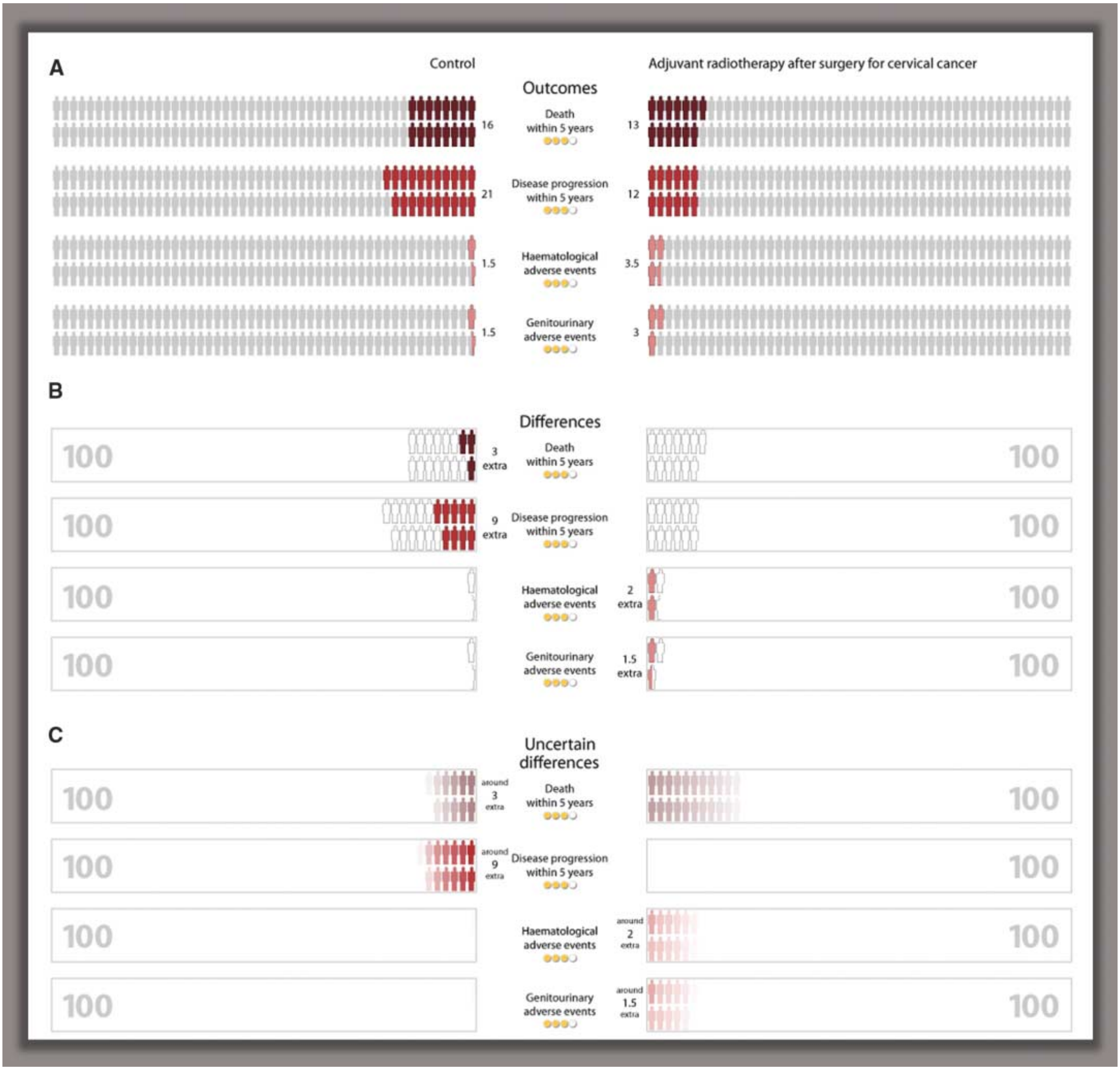

Fig. 6. Visualizations of potential benefits and harms of radiotherapy. (**A**) Expected outcomes for 100 women treated with adjuvant radiotherapy compared to 100 not treated. The three yellow dots indicate the evidence is of "moderate quality" using the GRADE scale. (**B**) Expected benefits and harms of treating 100 women with adjuvant radiotherapy; for example, we would expect 3 fewer deaths, 9 fewer women with disease progression, but extra adverse events. Whether the treatment is acceptable to a woman can depend on how she balances these benefits and harms. (**C**) Uncertainty about benefits and harms of treating 100 women, based on evidence from a Cochrane Collaboration review (*56*), using increased saturation of color to indicate greater certainty. The great uncertainty about the mortality benefit of adjuvant radiotherapy is clear.

the white cone. The figure does not communicate relative risks, and some commentators and members of the public tended to over focus on the most likely path, which is said to have unduly influenced evacuation decisions (*40*). Uncertainty on maps can also be represented using hue and saturation of color, blurring, symbols, and other techniques (*41*).

There is some empirical evidence (*42*) for the effectiveness of color in conveying information about variation in probability across a region. For example, fig. S5 displays the probability contours for strong winds over Northern Europe 42 hours ahead. Colored probability contours can be translated into other applications. The Bank of England's Monetary Policy Committee communicates probabilistic projections of inflation and output as fan charts; Fig. 5E shows an example of projections from November 2007 onward for changes in gross domestic product, with different shades indicating probability intervals. The central interval represents 10% probability, and the largest interval 90% probability, using a frequency interpretation assuming "economic circumstances identical to today's were to prevail on 100 occasions" (*43*). Despite criticism by journalists, the bank has always refused to include a numerical central estimate when first releasing the graphic each quarter-year, and this seems appropriate given the concerns described above about the "cone of uncertainty." Incidentally, the true series subsequently plummeted out of the 90% interval and off the bottom of the chart.

Using shading to represent probability is unsuitable for fine quantitative comparisons (*44*). Instead, the U.K. Climate Projections graphic (Fig. 5F) displays a full probability density function placed contiguous to a cumulative probability distribution, following recommended practice for well-educated audiences (*45*). Although interpretation of survival curves (the inverse of cumulative distribution functions) by nonprofessionals is feasible, it has been found to be strongly dependent on instruction (*13*). In this figure, as with all the figures discussed in this section, there is limited empirical evidence of the effectiveness of the various display formats for improving understanding.

Infographics

Increasing availability of online data and public interest in quantitative information has led to a golden age of infographics (i.e., graphical representations of data intended for a nontechnical audience), as championed by such American and British newspapers as *The New York Times* and *The Guardian* and by web sites such as IBM's Many Eyes (*46*), which allows visitors to create their own visualizations. The infographics movement has been greatly influenced by the minimalist design approach of Tufte (*28*), who emphasizes a lack of clutter, clean lines, and close attention to composition and color. The work of designers such as Fry (*47*) and McCandless (*48*) is as much art as science, with a strong creative element (based on a personal viewpoint) but a lack of empirical evaluation.

Recent innovations in infographics can be adapted to communicate uncertainty; for example, events can be represented in a word cloud, with font size proportional to probability. This technique is used in fig. S6, which shows those contestants who are most likely to win the Wimbledon 2011 men's singles tournament. The same information is communicated by a "tree map" in fig. S7, in which a large rectangle representing 100% is subdivided into small labeled rectangles whose areas represent the probabilities of the labeled events.

There is huge potential for infographics with interactive features. A striking example is Rosling's Gapminder (*49*), which has influenced the development of animation of large and complex data sets in which interactivity is encouraged, and controlled movement is generally used to represent changes over time. There are several benefits claimed for interactive over static visualizations (*14*, *50*). Understanding and retention are promoted by interactive graphics because the user is encouraged to engage with the content actively rather than passively, which can also help to counteract differences in numeracy (*51*). Components such as tool-tip hints and hyperlinks allow optional explanation and multiple representations. Interactive graphics can adapt to the user's abilities and preferences (*50*) and can offer feedback and assessment. For instance, zooming facilities, used in applications such as the U.S. Riskometer (*52*), focus attention on low-probability events. We have developed an interactive animated version of Nightingale's roses (movie S1), as well as animations for comparing multiple formats of representing risks (movie S2) and the type of screening test discussed previously in Fig. 4 (movie S3).

General use of interactive graphics may, however, be limited through lack of user skills and software incompatibility. Tellingly, Bostrom and Lofstedt remarked (*53*) that modern information technologies and the internet "provide unprecedented opportunities, both for supporting risk decision making and for manipulating unsuspecting users."

What If We're Uncertain About the Probabilities?

Uncertainty about probabilities can arise from statistical error, ambiguous or limited data, oversimplification of complex risk information, scientific disagreement, and ignorance (*54*). There is no consensus on either the benefit or optimum means of communicating such uncertainty. Moreover, research indicates that although some people may welcome additional acknowledgement of ambiguity, others—particularly those with low numeracy or low optimism—may become confused, suspicious, and more risk-averse (*54*, *55*).

Statistical sampling error can be communicated using the techniques on visualizing continuous probability distributions outlined earlier. One method for communicating to patients the potential benefits and harms of a treatment is illustrated in Fig. 6. The information used in this figure is taken from a review by the Cochrane Collaboration on adjuvant radiotherapy after surgery for cancer of the cervix (*56*) (see also Fig. 5C). The probabilities of different outcomes are represented by stacked icons, heavily influenced by Neurath's Isotypes.

Because the outcomes in Fig. 6A are not mutually exclusive, 100 women are displayed in each bar, allowing part-to-whole comparisons. The data from Fig. 6A are filtered in Fig. 6B to leave only the positive and negative aspects of the health care intervention. Finally, Fig. 6C is an optional representation, which includes a measure of uncertainty by fading the intensity of shading of the icons. The yellow dots in Fig. 6 indicate GRADE assessments, which are standard practice in the Cochrane Collaboration and other organizations to express a judgment as to the quality of the underlying evidence (*57*). GRADE is based on the extent to which the authors of the review expect the estimates of the benefits and harms of a treatment to change when more evidence is received. This feature is arguably more important than representations of statistical sampling error.

What Further Research Is Needed?

In 2003, Bostrom and Lofstedt (*53*) concluded that risk communication was "still more art than science, relying as it often does in practice on good intuition rather than well-researched principles." There has been limited progress since then, and existing reviews lament the poor research base in this area, with many small studies carried out on students (*15*) or self-selected samples, little exploration of cumulative risk information, and contradictory findings. Larger and more sophisticated randomized experiments would

Box 1. What is the best way to visualize probabilistic uncertainty?

The most suitable choice of visualization to illustrate uncertainty depends closely on the objectives of the presenter, the context of the communication, and the audience. Visschers *et al.* (*15*) concluded that the "task at hand may determine which graph is most appropriate to present probability information" and it is "not possible to formulate recommendations about graph types and layouts." Nonetheless, if we aim to encourage understanding rather than to just persuade, certain broad conclusions can be drawn, which hold regardless of the audience.

- Use multiple formats, because no single representation suits all members of an audience.
- Illuminate graphics with words and numbers.
- Design graphics to allow part-to-whole comparisons, and choose an appropriate scale, possibly with magnification for small probabilities.
- To avoid framing bias, provide percentages or frequencies both with and without the outcome, using frequencies with a clearly defined denominator of constant size.
- Helpful narrative labels are important. Compare magnitudes through tick marks, and clearly label comparators and differences.
- Use narratives, images, and metaphors that are sufficiently vivid to gain and retain attention, but which do not arouse undue emotion. It is important to be aware of affective responses.
- Assume low numeracy of a general public audience and adopt a less-is-more approach by reducing the need for inferences, making clear and explicit comparisons, and providing optional additional detail.
- Interactivity and animations provide opportunities for adapting graphics to user needs and capabilities.
- Acknowledge the limitations of the information conveyed in its quality and relevance. The visualization may communicate only a restricted part of a whole picture.
- Avoid chart junk, such as three-dimensional bar charts, and obvious manipulation through misleading use of area to represent magnitude.
- Most important, assess the needs of the audience, experiment, and test and iterate toward a final design.

help assess preferences and understanding of appropriate choices of formats for different audiences, and could also indicate the extent to which the claimed biases concerning quantitative information (*6*) are due to inappropriate presentations (*22*).

Given the importance of the public understanding of health, economic, and environmental risk, it may appear remarkable that so little firm guidance can be given about how best to communicate uncertainty. But this is perhaps unsurprising given the complexity of influences operating in any particular context, and suggests that, even more than experimentation, we need careful case studies describing the development and evaluation of specific examples in a range of contexts (Box 1).

What About Deeper Uncertainties?

Many hazards facing society are subject to deeper uncertainties than are reflected in probabilities and measures of statistical error. Counterterrorism, climate change, pesticides, deep-sea drilling, and nuclear waste disposal are often characterized by fundamental disagreements, and even ignorance, about the likelihood and values of different consequences, as well as by essential indeterminacy about a future governed by human behavior. People's understanding of these hazards depends on their beliefs about how the world works (*58*) and how society should be ordered (*59*). Here a language of caution and humility is appropriate, and decisions are sought that are robust, resilient, and can adapt to possible future surprises (*60*, *61*).

Guidance for handling uncertainty in the next IPCC review formalizes how the precision with which uncertainties are expressed should depend on the quality of evidence and scientific agreement (*62*). But such deeper uncertainties do not readily translate into visualizations. In fact, the more attractive a depiction is made, the more people may believe it represents the whole truth rather than being a construction of limited knowledge and judgment. So perhaps the greatest challenge is to make a visualization that is attractive and informative, and yet conveys its own contingency and limitations.

References and Notes

1. G. F. Gigerenzer, *The Intelligence of the Unconscious* (Viking, New York, 2007).
2. P. Slovic, E. Peters, M. L. Finucane, D. G. Macgregor, *Health Psychol.* **24** (suppl.), S35 (2005).
3. B. de Finetti, *Theory of Probability* (Wiley, London, 1974).
4. F. Nightingale, *Notes on Matters Affecting the Health, Efficiency and Hospital Administration of the British Army, Founded Chiefly on the Experience of the Late War* (Harrison, London, 1858).
5. Works of O. Neurath and M. Neurath, Isotype Institute (available at www.fulltable.com/iso/).
6. D. Kahneman, P. Slovic, A. Tversky, *Judgment Under Uncertainty: Heuristics and Biases* (Cambridge Univ. Press, Cambridge, 2006).
7. E. Peters, J. Hibbard, P. Slovic, N. Dieckmann, *Health Aff.* **26**, 741 (2007).
8. A. Fagerlin, P. A. Ubel, D. M. Smith, B. J. Zikmund-Fisher, *Am. J. Health Behav.* **31** (suppl. 1), S47 (2007).
9. D. E. Nelson, B. W. Hesse, R. T. Croyle, *Making Data Talk: Communicating Public Health Data to the Public, Policy Makers, and the Press* (Oxford Univ. Press, New York, ed. 1, 2009).
10. C. Skubisz, T. Reimer, U. Hoffrage, in *Communication Yearbook 33* (Routledge, London, 2009), pp. 177–211.
11. J. S. Ancker, Y. Senathirajah, R. Kukafka, J. B. Starren, *J. Am. Med. Inform. Assoc.* **13**, 608 (2006).
12. I. M. Lipkus, J. G. Hollands, *J. Natl. Cancer Inst. Monogr.* **1999**, 149 (1999).
13. I. M. Lipkus, *Med. Decis. Making* **27**, 696 (2007).
14. A. Bostrom, L. Anselin, J. Farris, *Ann. N.Y. Acad. Sci.* **1128**, 29 (2008).
15. V. H. M. Visschers, R. M. Meertens, W. W. F. Passchier, N. N. K. de Vries, *Risk Anal.* **29**, 267 (2009).
16. T. S. Wallsten, D. V. Budescu, A. Rapoport, R. Zwick, B. Forsyth, *J. Exp. Psychol. Gen.* **155**, 348 (1986).
17. Intergovernmental Panel on Climate Change Working Group 1, *IPCC Fourth Assessment Report: The Physical Science Basis* (IPCC, 2007; www.ipcc.ch/ipccreports/ar4-wg1.htm).
18. M. Galesic, R. Garcia-Retamero, *Arch. Intern. Med.* **170**, 462 (2010).
19. G. Gigerenzer, W. Gaissmaier, E. Kurz-Milcke, L. M. Schwartz, S. Woloshin, *Psychol. Sci. Public Interest* **8**, 53 (2007).
20. B. J. McNeil, S. G. Pauker, H. C. Sox Jr., A. Tversky, *N. Engl. J. Med.* **306**, 1259 (1982).
21. R. Morss, J. Demuth, J. Lazo, *Weather Forecast.* **23**, 974 (2008).
22. E. Kurz-Milcke, G. Gigerenzer, L. Martignon, *Ann. N.Y. Acad. Sci.* **1128**, 18 (2008).
23. V. F. Reyna, C. J. Brainerd, *Learn. Individ. Differ.* **18**, 89 (2008).
24. V. Denes-Raj, S. Epstein, *J. Pers. Soc. Psychol.* **66**, 819 (1994).
25. R. Garcia-Retamero, M. Galesic, G. Gigerenzer, *Med. Decis. Making* **30**, 672 (2010).
26. W. P. Neace, S. Michaud, L. Bolling, K. Deer, L. Zecevic, *Judgm. Decis. Mak.* **3**, 140 (2008).
27. S. L. Joslyn, R. M. Nichols, *Meteorol. Appl.* **16**, 309 (2009).
28. E. Tufte, *The Visual Display of Quantitative Information* (Graphics Press, Cheshire, CT, 2001).
29. C. M. R. Smerecnik *et al.*, *Risk Anal.* **30**, 1387 (2010).
30. S. Woloshin, L. M. Schwartz, A. Ellner, *BMJ* **327**, 695 (2003).
31. NASA Space Shuttle Safety and Mission Assurance Office, NASA Review of Shuttle Risks (available at http://hw.libsyn.com/p/3/0/a/30aafb8c2337eb80/NASAShuttleRiskReview-excerpt.pdf).
32. B. J. Zikmund-Fisher, A. Fagerlin, P. A. Ubel, *Cancer* **113**, 3382 (2008).
33. M. Galesic, R. Garcia-Retamero, G. Gigerenzer, *Health Psychol.* **28**, 210 (2009).
34. J. S. Ancker, E. U. Weber, R. Kukafka, *Med. Decis. Making* **31**, 143 (2011).
35. Breast Screening—Performance of Mammography: Cancer Research UK (available at http://info.cancerresearchuk.org/cancerstats/types/breast/screening/mammography/).
36. J. G. Dolan, S. Iadarola, *BMC Med. Inform. Decis. Mak.* **8**, 14 (2008).
37. C. Keller, M. Siegrist, V. Visschers, *Risk Anal.* **29**, 1255 (2009).
38. A. P. Sokolov *et al.*, *J. Clim.* **22**, 5175 (2009).
39. J. Sanyal, S. Zhang, G. Bhattacharya, P. Amburn, R. J. Moorhead, *IEEE Trans. Vis. Comput. Graph.* **15**, 1209 (2009).
40. K. Broad *et al.*, Misinterpretations of the "Cone of Uncertainty" in Florida During the 2004 Hurricane Season (2010) (available at http://journals.ametsoc.org/doi/abs/10.1175/BAMS-88-5-651).
41. A. M. MacEachren *et al.*, *Cartogr. Geogr. Inform. Sci.* **32**, 139 (2005).
42. M. Leitner, B. P. Buttenfield, *Cartogr. Geogr. Inform. Sci.* **27**, 3 (2000).
43. Bank of England, Bank of England Inflation Report 2007 (available at www.bankofengland.co.uk/publications/inflationreport/2007.htm).
44. W. S. Cleveland, R. McGill, *Science* **229**, 828 (1985).
45. H. Ibrekk, M. G. Morgan, *Risk Anal.* **7**, 519 (1987).
46. Many Eyes (available at www-958.ibm.com/software/data/cognos/manyeyes/).
47. B. Fry, Writing (available at http://benfry.com/writing/).
48. D. McCandless, *Information is Beautiful* (Collins, London, 2010).
49. H. Rosling, Gapminder: Unveiling the beauty of statistics for a fact based world view (available at www.gapminder.org/).
50. V. J. Strecher, T. Greenwood, C. Wang, D. Dumont, *J. Natl. Cancer Inst. Monogr.* **1999**, 134 (1999).
51. J. S. Ancker, E. U. Weber, R. Kukafka, *Med. Decis. Making* **31**, 130 (2011).
52. American Council on Science and Health, Riskometer and RiskRings (available at http://riskometer.org/).
53. A. Bostrom, R. E. Löfstedt, *Risk Anal.* **23**, 241 (2003).
54. M. C. Politi, P. K. J. Han, N. F. Col, *Med. Decis. Making* **27**, 681 (2007).
55. P. K. J. Han *et al.*, *Med. Decis. Making* **31**, 354 (2011).
56. L. Rogers, S. S. N. Siu, D. Luesley, A. Bryant, H. O. Dickinson, in *Cochrane Database of Systematic Reviews*, The Cochrane Collaboration, L. Rogers, Eds. (Wiley, Chichester, UK, 2009).
57. G. H. Guyatt *et al.*; GRADE Working Group, *BMJ* **336**, 924 (2008).
58. M. G. Morgan, B. Fischhoff, A. Bostrom, C. J. Atman, *Risk Communication: A Mental Models Approach* (Cambridge Univ. Press, Cambridge, ed. 1, 2001).
59. D. Kahan, *Nature* **463**, 296 (2010).
60. A. Stirling, *Nature* **468**, 1029 (2010).
61. G. Morgan *et al.*, *Best Practice Approaches for Characterizing, Communicating, and Incorporating Scientific Uncertainty in Decisionmaking* (U.S. Climate Change Science Program, 2009; www.climatescience.gov/Library/sap/sap5-2/final-report/default.htm).
62. IPCC, *Cross-Working Group Meeting on Consistent Treatment of Uncertainties, Guidance Note for Lead Authors of the IPCC Fifth Assessment Report on Consistent Treatment of Uncertainties* (2010) (available at www.ipcc-wg2.gov/meetings/CGCs/Uncertainties-GN_IPCCbrochure_lo.pdf).
63. G. Williams, *Women and Work* (Nicholson & Watson, London, 1945).
64. Kick Off—Football Stats—Match Previews (available at www.kickoff.co.uk/).
65. Harvard School of Public Health Disease Risk Index (available at www.diseaseriskindex.harvard.edu/update/).
66. Adjuvant! Online (available at http://adjuvantonline.com/index.jsp).
67. Genetic Testing for Carrier Status, Disease Risk and Drug Response—23andMe (available at www.23andme.com/health/risks/).
68. MIT Global Change Program | Greenhouse Gamble (available at http://globalchange.mit.edu/resources/gamble/).
69. Met Office, Invent—Weather: Text view—Location: Peterborough (available at www.metoffice.gov.uk/public/pws/invent/weathertext/index.html?310120).
70. Definition of the NHC Track Forecast Cone (available at www.nhc.noaa.gov/aboutcone.shtml).
71. UK Climate Projections—What is UKCP09: Probability (available at http://ukclimateprojections.defra.gov.uk/content/view/1205/618/).
72. Full permission statement for Fig. 3C: Reprinted with permission. © 2008 American Society of Clinical Oncology. Full permission statement for Fig. 3D: © 23andMe, Inc. 2008-2011. All rights reserved; distributed pursuant to a Limited License from 23andMe. Full permission statement for Fig. 5C: Copyright Cochrane Collaboration, reproduced with permission. Full permission statement for Fig. 5F: © Crown Copyright 2009. The UK Climate Projections (UKCP09) have been made available by the Department for Environment, Food and Rural Affairs (Defra) and the Department of Climate Change (DECC) under licence from the Met Office, UK Climate Impacts Programme, British Atmospheric Data Centre, Newcastle University, University of East Anglia, Environment Agency, Tyndall Centre and Proudman Oceanographic Laboratory. These organizations give no warranties, express or implied, as to the accuracy of the UKCP09 and do not accept any liability for loss or damage that may arise from reliance upon the UKCP09; any use of the UKCP09 is undertaken entirely at the users risk.

Acknowledgments: Supported by an endowment from the Winton Charitable Foundation (D.S., M.P.).

Supporting Online Material

www.sciencemag.org/cgi/content/full/333/6048/1393/DC1
Figs. S1 to S7
Movies S1 to S3
References (*73*, *74*)

10.1126/science.1191181