

How do people deal with uncertainty in models?

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**Advanced Water Education Workshop:
Using Models to Simplify the Complex Interactions
of Water in the Valley
July 10 and 11, 2013**



educators at all levels
recognize the need to teach
students to understand
complex systems that are
interactive, dynamic and
hierarchical

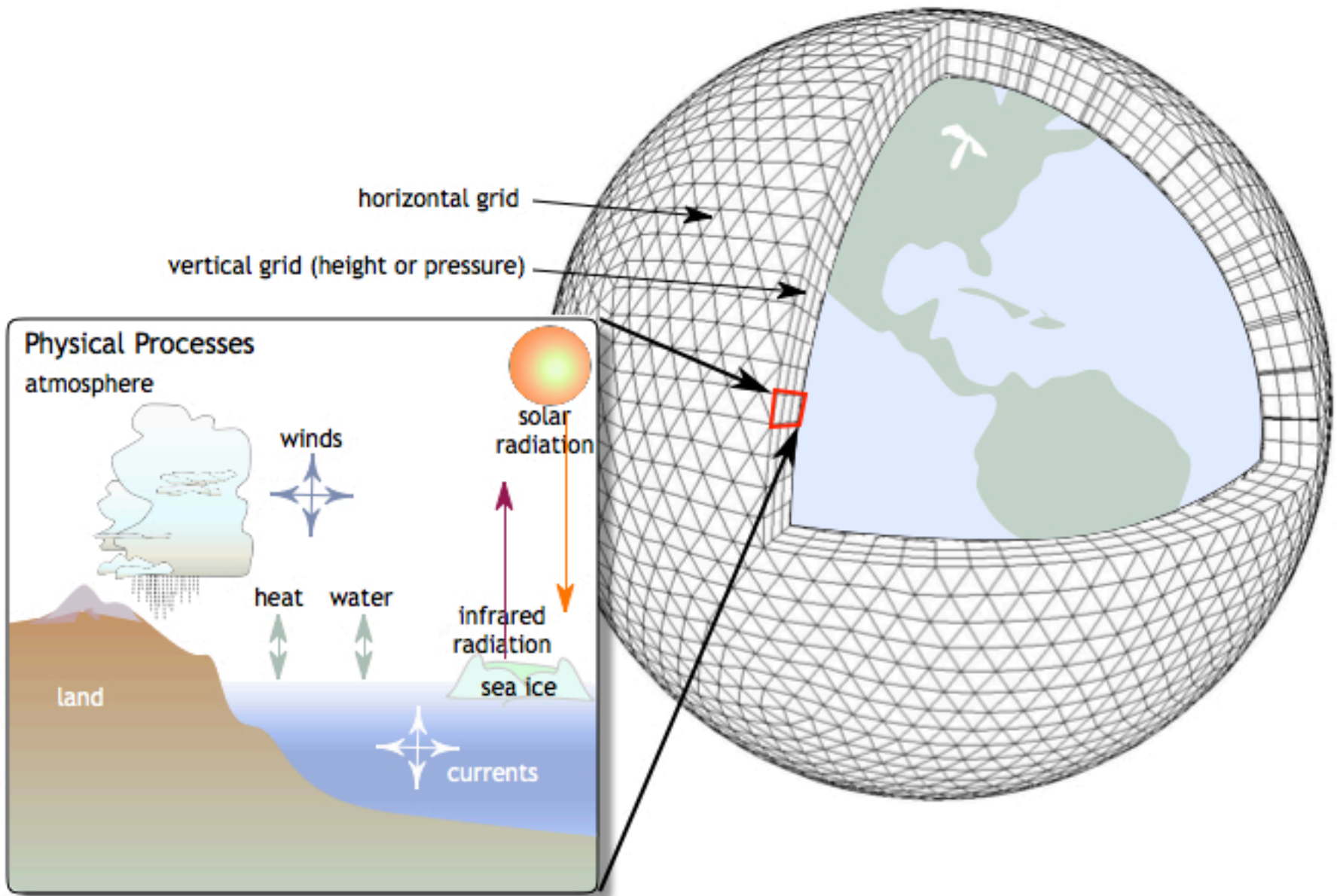


models are increasingly
used to represent,
understand, and
communicate complex
systems



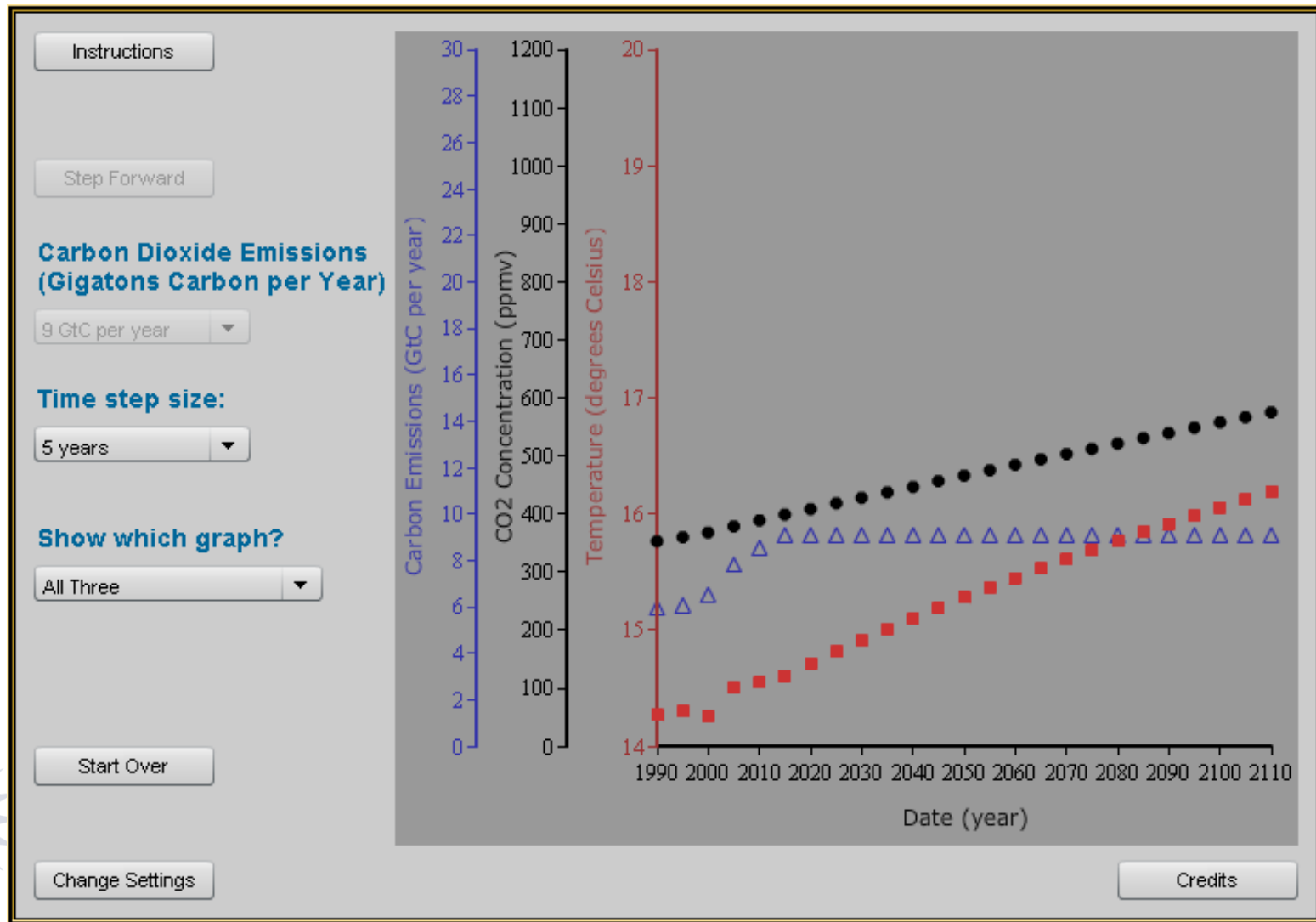
models are recognized as an
integral tool for
understanding complex
systems – such as the **water
and climate systems** – and
for education and decision
making





<http://www.cmmmap.org/learn/modeling/whats2.html>

The Very, Very Simple Climate Model Activity



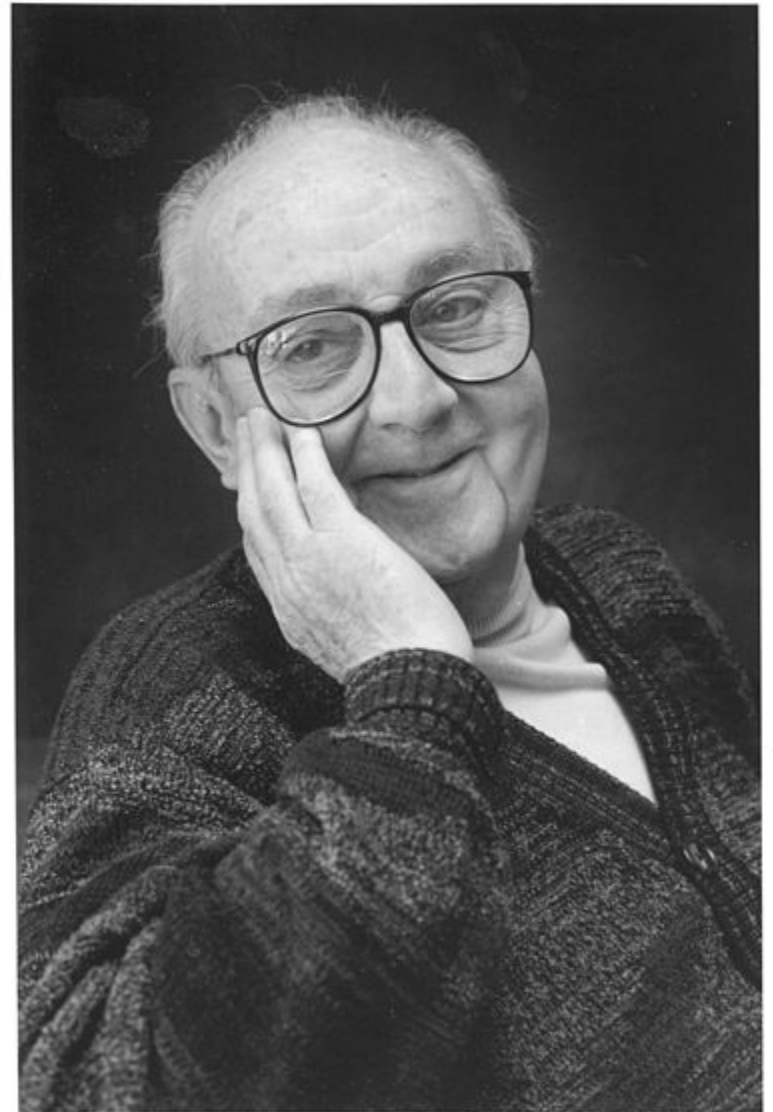
<http://spark.ucar.edu/activity/very-very-simple-climate-model-activity>

efforts to enhance the contributions of water and climate models to decision making, however, have met with **mixed success**



Essentially, all
models are
wrong, but
some are
useful.

- George E. P. Box



one major challenge stems
from differences in how
scientists and decision
makers understand,
communicate and visualize
uncertainty



Uncertainty (Pielke, 2007)

- *In a particular situation more than one outcome is consistent with our expectations*
 - Ignorance - We simply do not know – is fundamentally irreducible
 - Risk – We know the probability distributions of possible outcomes – is quantifiable
- Objective uncertainty – complete and accurate characterizations of the entire set of outcomes associated with a particular set of expectations
- Subjective uncertainty – our judgments about how to characterize the entire set of outcomes
- In almost all situations outside closed systems, science is limited to providing a rigorous, formalized expression of subjective uncertainties

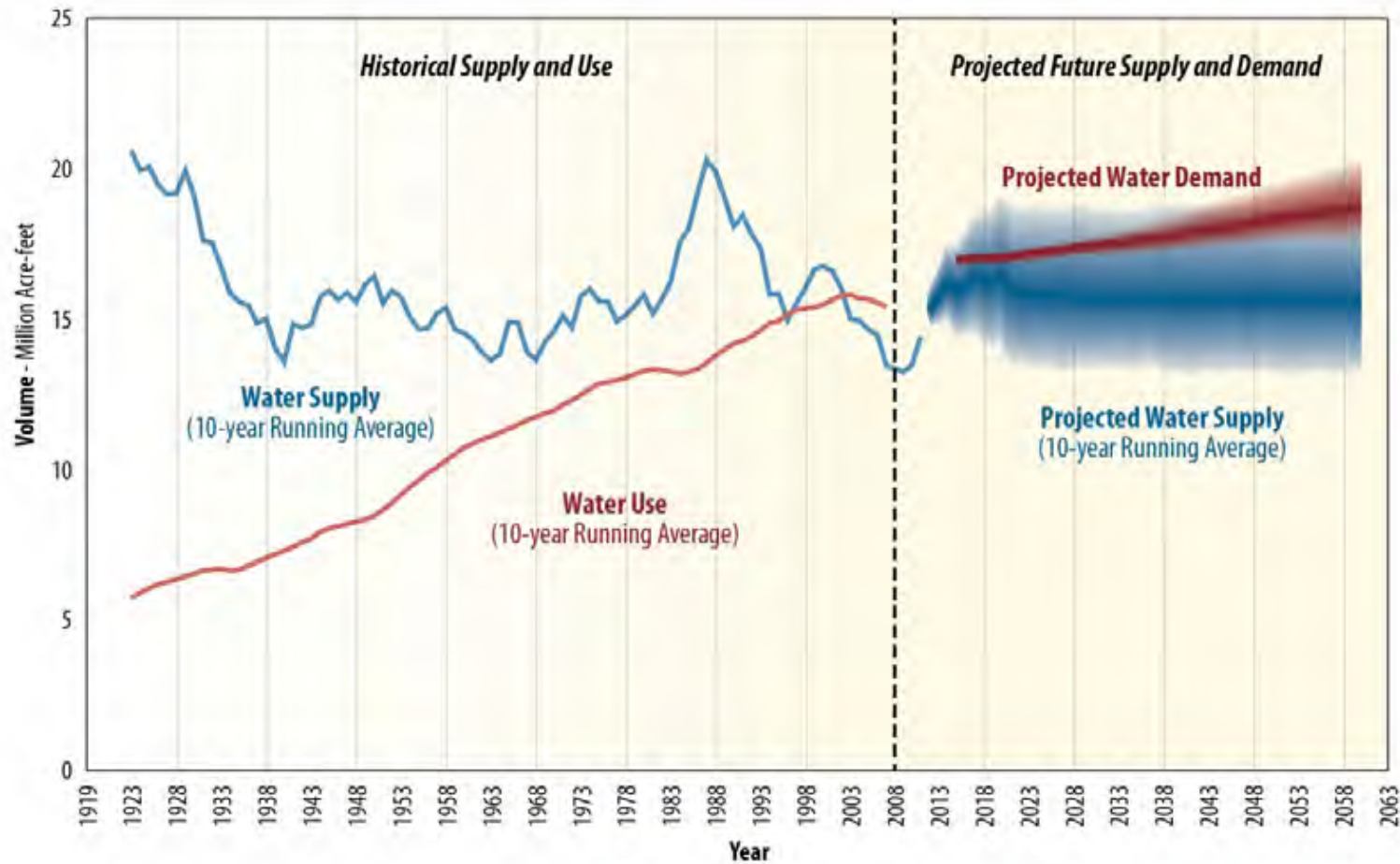


HURRICANE CENTRAL

HURRICANE SANDY

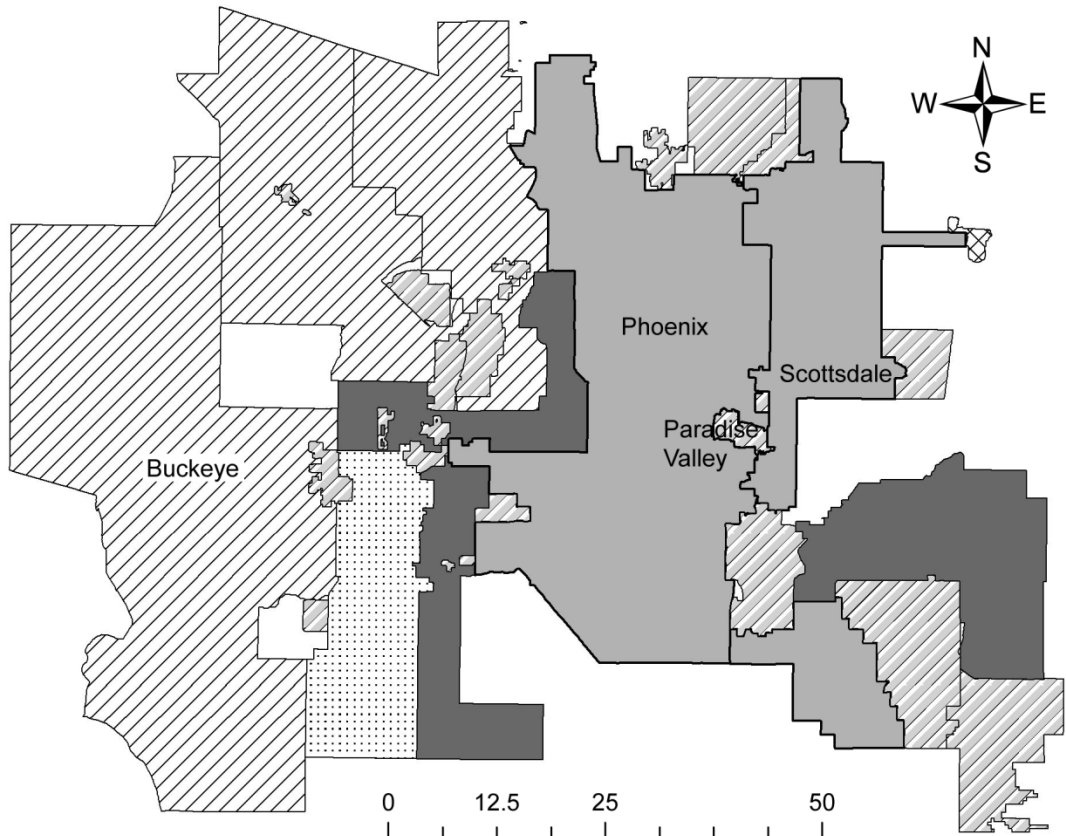


FIGURE 2
Historical Supply and Use¹ and Projected Future Colorado River Basin Water Supply and Demand¹

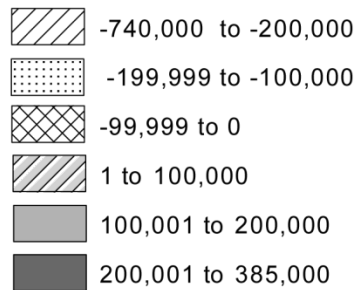


¹ Water use and demand include Mexico's allotment and losses such as those due to reservoir evaporation, native vegetation, and operational inefficiencies.

Bureau of Reclamation. (2012). Colorado River Basin Water Supply and Demand Study: Study Report (pp. 89). Boulder City, NV: U. S. Department of Interior, Bureau of Reclamation.



Average Across Scenarios
of Net Potential Growth

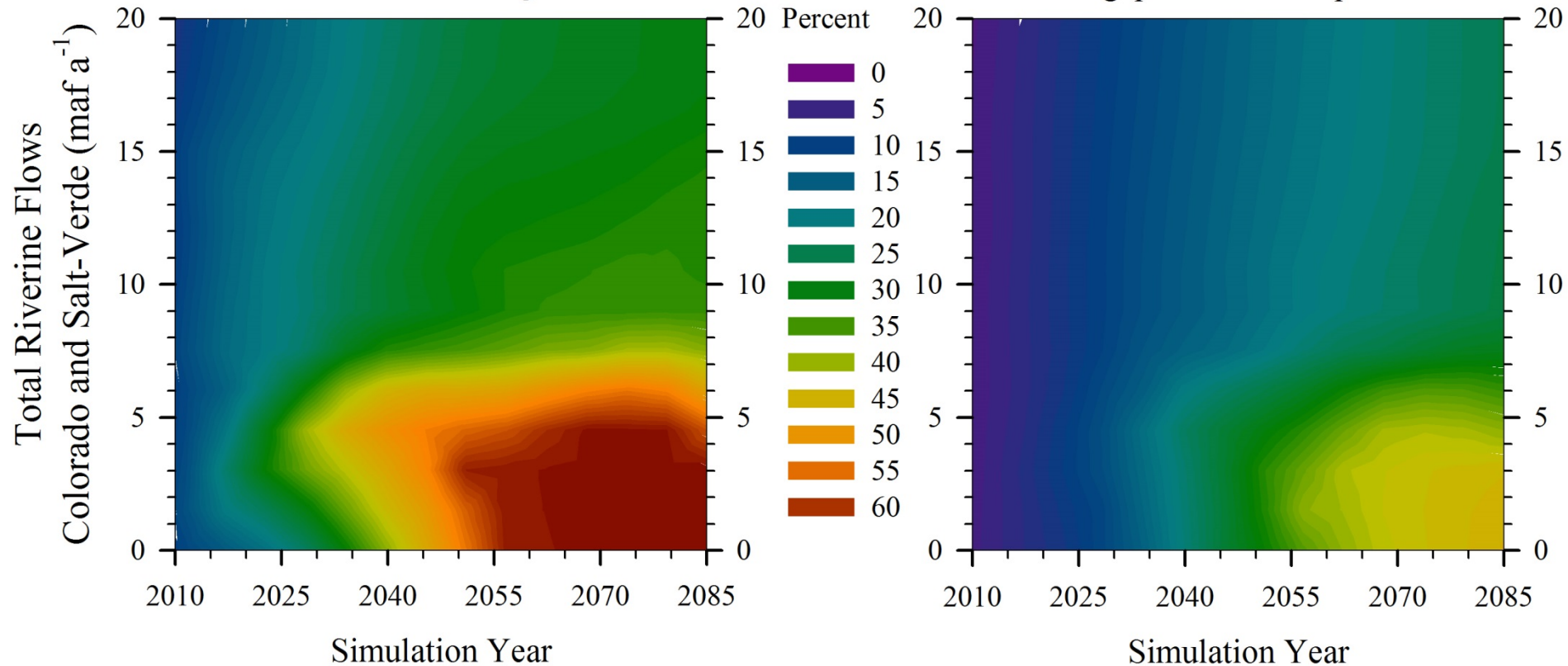


Scenario Analysis

% Annual Demand (regional) Met by Groundwater

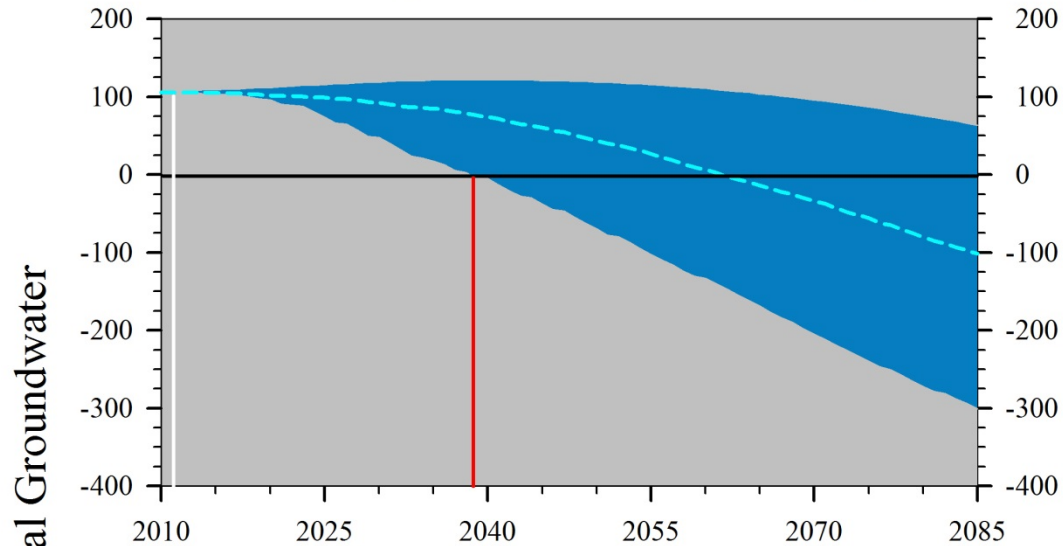
Scenario: Strong Groundwater and Demand Management

Scenario: Water Infrastructure for Megapolitan Development

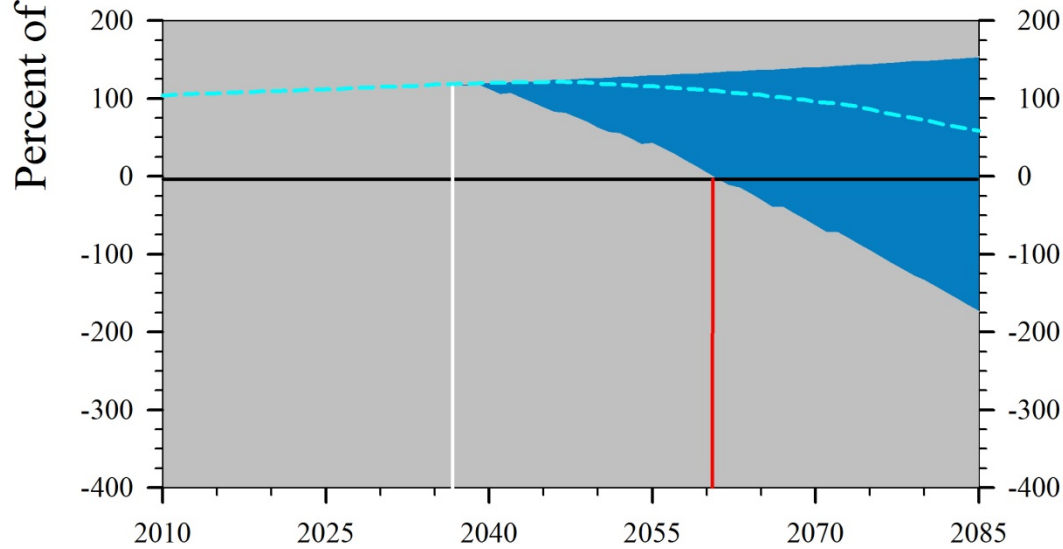


Case Example: Phoenix, Arizona

Scenario: Strong Groundwater and Demand Management



Scenario: Water Infrastructure for Megapolitan Development



Simulation Year



scientists tend to frame
uncertainty in probabilistic
terms and communicate
uncertainty through
statistical methods



whereas decision makers
may also frame uncertainty
in **political terms** based on
perceived costs of being
wrong



while uncertainty is being reduced in some climate science domains, **uncertainty is increasing** in other areas



“The uncertainty in AR5’s climate predictions and projections will be much greater than in previous IPCC reports...”



More knowledge, less certainty

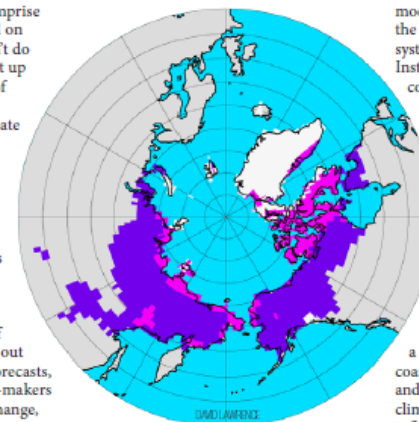
KEVIN TRENBERTH

Major efforts are underway to improve climate models both for the advancement of science and for the benefit of society. But early results could cause problems for the public understanding of climate change.

The climate scientists that comprise the Intergovernmental Panel on Climate Change (IPCC) don’t do predictions, or at least they haven’t up until now¹. Instead the scientists of the IPCC have, in the past, made projections of how the future climate could change for a range of ‘what-if’ emissions scenarios. But for its fifth assessment report, known as AR5 and due out in 2013, the UN panel plans to examine explicit predictions of climate change over the coming decades. In AR5’s Working Group I report, which focuses on the physical science of climate change, one chapter will be devoted to assessing the skill of climate predictions for timescales out to about 30 years. These climate forecasts, which should help guide decision-makers on how to plan for and adapt to change, will no doubt receive much attention.

Another chapter will deal with longer-term projections, to 2100 and beyond, using a suite of global models. Many of these models will attempt new and better representations of important climate processes and their feedbacks — in other words, those mechanisms that can amplify or diminish the overall effect of increased incoming radiation. Including these elements will make the models into more realistic simulations of the climate system, but it will also introduce uncertainties.

So here is my prediction: the uncertainty in AR5’s climate predictions and projections will be much greater than in previous IPCC reports, primarily because of the factors noted above. This could present a major problem for public understanding of climate change. Is it not a reasonable expectation that as knowledge and understanding increase over time, uncertainty should decrease? But while our knowledge of certain factors does increase, so does our understanding of factors we previously did not account for or even recognize.



Climate models project large decreases in permafrost by 2100. Some models used for the IPCC’s next assessment will include important feedbacks associated with increased releases of the greenhouse gases methane and carbon dioxide. Image adapted from ref. 9.

FROM PROJECTION TO PREDICTION

In previous IPCC assessments¹, changes in the atmospheric concentrations of greenhouse gases and aerosols over time were gauged using ‘idealized emissions scenarios’, which are informed estimates of what might happen in the future under various sets of assumptions related to population, lifestyle, standard of living, carbon intensity and the like. Then the changes in future climate were simulated for each of these scenarios. The output of such modelling is usually referred to as a projection, rather than a prediction or a forecast. Unlike a weather prediction, the

models in this case are not initialized with the current or past state of the climate system, as derived from observations. Instead, they begin with arbitrary climatic conditions and examine only the change in projected climate, thereby removing any bias that could be associated with trying to realistically simulate the current climate as a starting point. This technique works quite well for examining how the climate could respond to various emissions scenarios in the long term.

Climate models have, however, improved in the past few years, and society is now demanding ever more accurate information from climate scientists. Faced with having to adapt to a range of possible impacts, policymakers, coastal planners, water-resource managers and others are keen to know how the climate will change on timescales that influence decision-making. Because the amount of warming that will take place up to 2030 is largely dependent on greenhouse gases that have already been released into the atmosphere, it is theoretically possible to predict, with modest skill, how the climate will respond over this time period.

In recent years, several modelling groups have published such predictions for the coming decades²⁻⁴ (Fig. 1). In weather prediction, and in this newer form of climate prediction, it is essential to start the model with the current state of the system. This is done by collecting observations of the atmosphere, oceans, land surface and soil moisture, vegetation state, sea ice and so forth, and assimilating these data into the models — which can be challenging, given model imperfections. Although important progress has been made in this area, the techniques are not yet fully established⁵. In part because it takes at least a decade to verify a 10-year forecast, evaluating and optimizing the models⁶ will be a time-consuming process. The spread in initial results is therefore bound to be large, and the uncertainties much larger, than for the

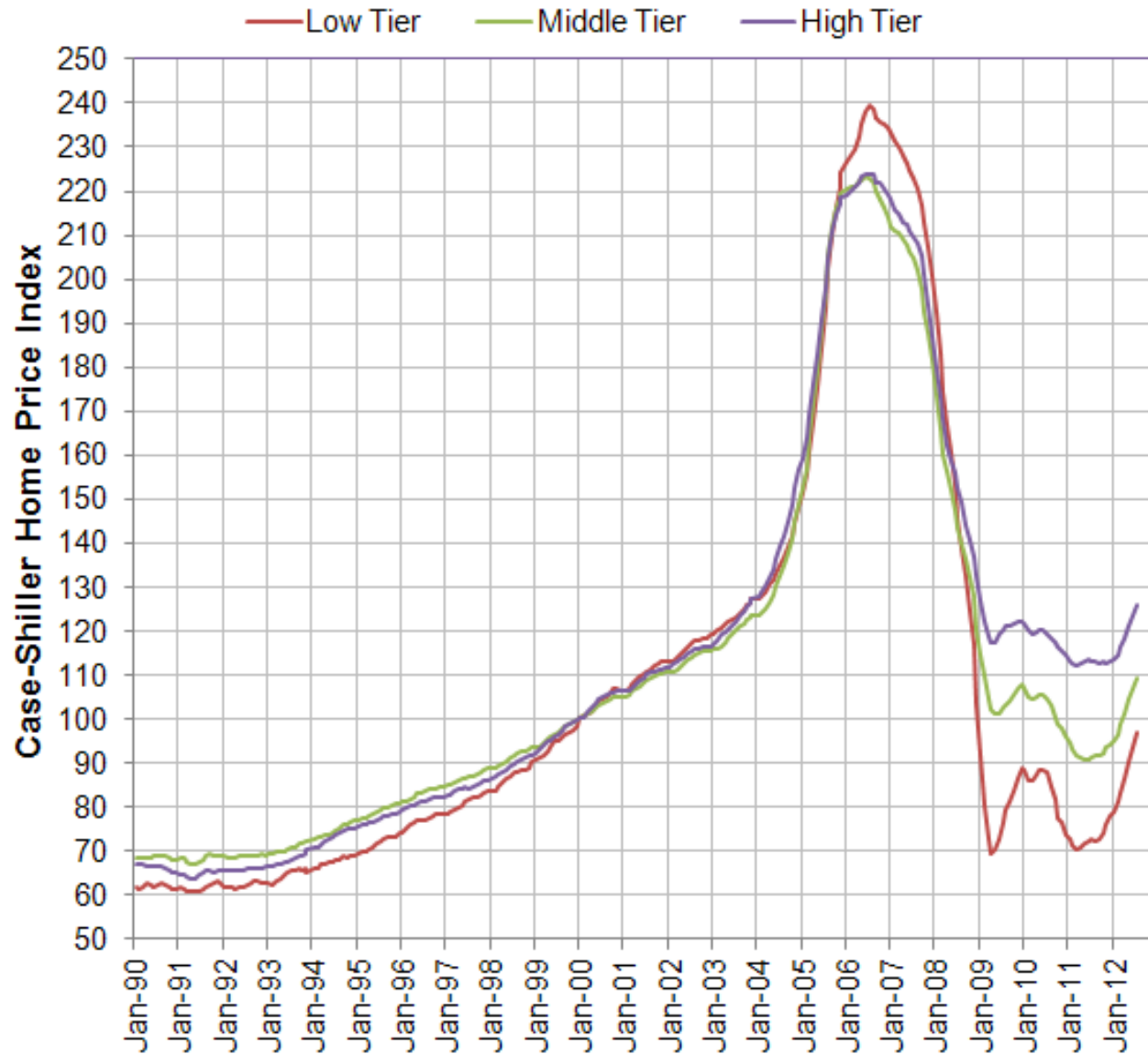
in addition to scientific
uncertainty, decision makers
must incorporate **social,**
political and economic
uncertainties



Case-Shiller Tiered Home Price Indices for Phoenix, AZ

January 1990 through July 2012

Index Value of 100 = January 2000



CONTEXT

Environmental

- Biophysical (climate, water supply, other ecological)
- Land Change (forest, urban, agriculture)

Social

- Institutional (political, governance, economic, organizational)
- Demand (demographics, technological)
- Interpersonal (trust, responsibility, tenure)

TYPE

Fundamental

- Epistemic
- Ontological

Ambiguity

- Normative
- Objective

Ignorance

- Recognized
- Purposeful
- Blind

Practical

- Too expensive
- Trade-offs

DIMENSIONS

Positioning

- Positive
- Negative
- Neutral

Urgency

- Short-term
- Long-term

Explicitness

- Explicit
- Implicit

Justification

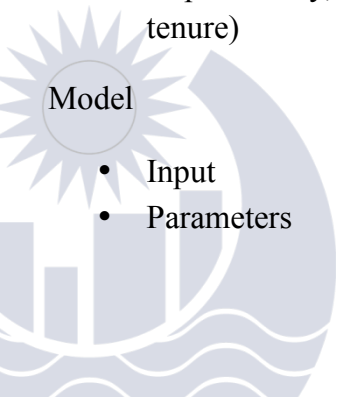
- Inaction
- Policy
- Deliberation
- Research

Reducibility

- Timeline
- Strategy
- Range
- Communication

DEPLOYMENT

- Attenuation
- Amplification
- Quantification Rhetoric
- Proliferation
- Transference
- Condensing
- Displacing
- Social Ordering



we need to help students to
learn to **frame, describe, and**
represent uncertainty



Techniques for Visualizing Uncertainty

- Use multiple formats, because no single representation suits all members of an audience.
- Illuminate graphics with words and numbers.
- Helpful narrative labels are important. Compare magnitudes through tick marks.
- Use narratives, images, and metaphors that are sufficiently vivid to gain and retain attention, but which do not arouse undue emotion.

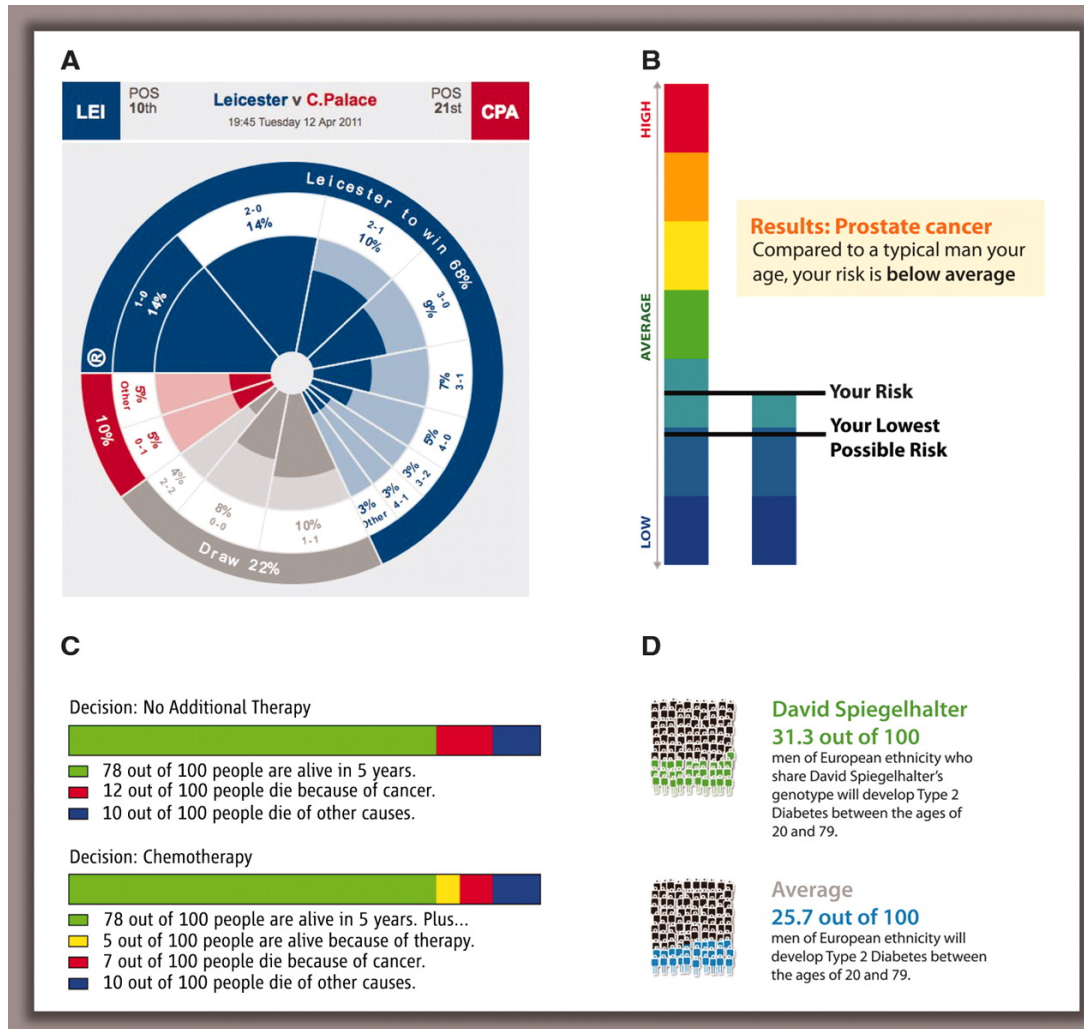


Techniques for Visualizing Uncertainty

- Interactivity and animations provide opportunities for adapting graphics to user needs and capabilities.
- 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.



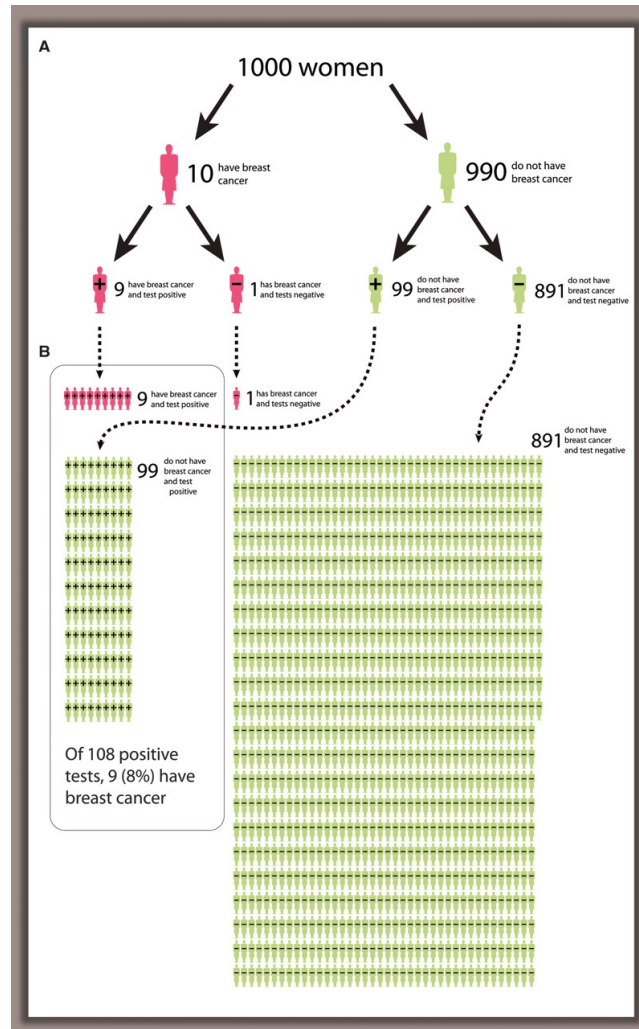
Fig. 3 Visualizations of probabilities for discrete events.



D Spiegelhalter et al. Science 2011;333:1393-1400

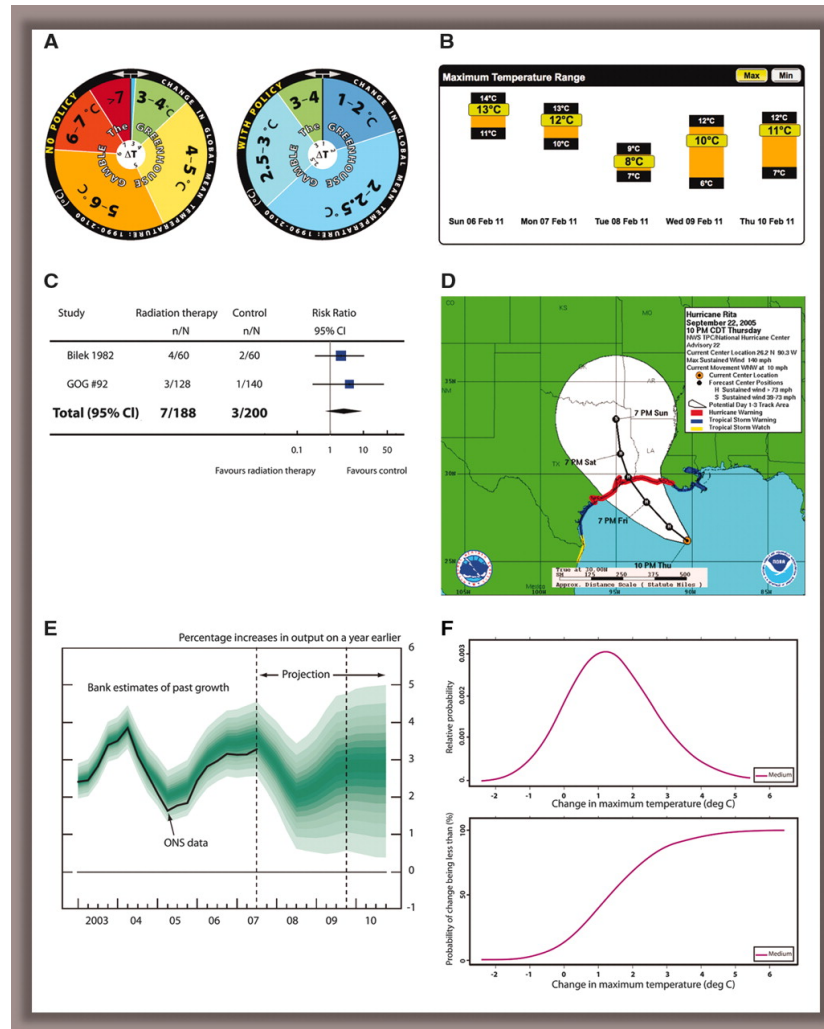


Fig. 4 Visualizations of the predictive accuracy of a screening test.



D Spiegelhalter et al. Science 2011;333:1393-1400

Fig. 5 Visualizations of probability distributions for continuous quantities.



D Spiegelhalter et al. Science 2011;333:1393-1400

“...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.”



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