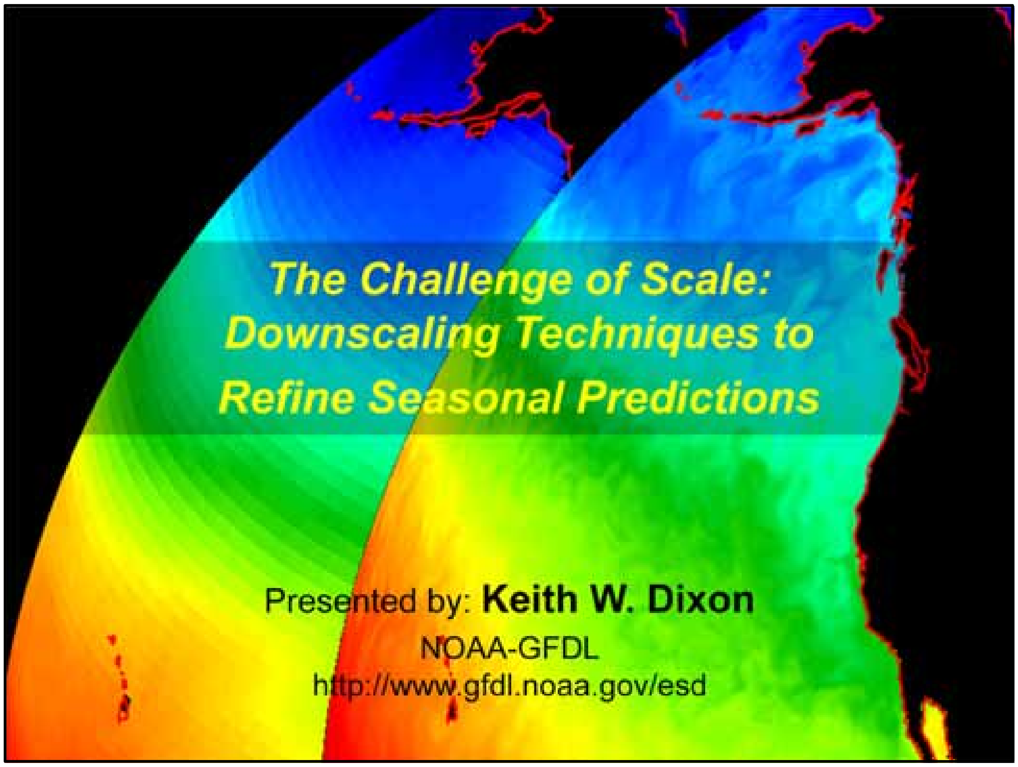

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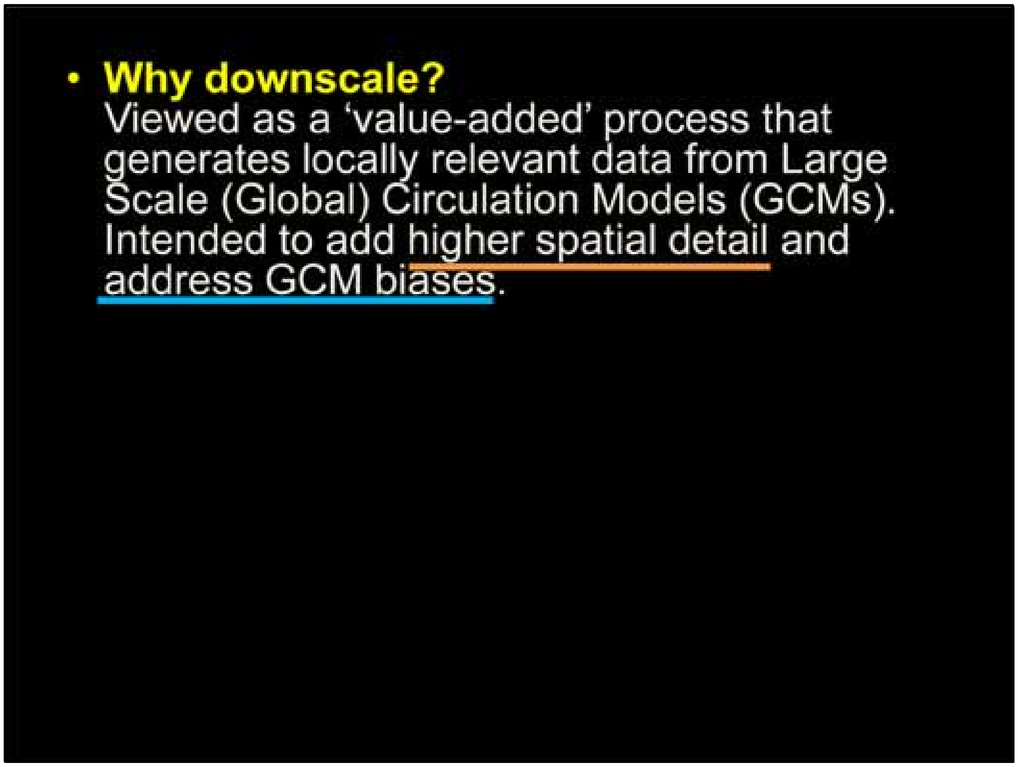
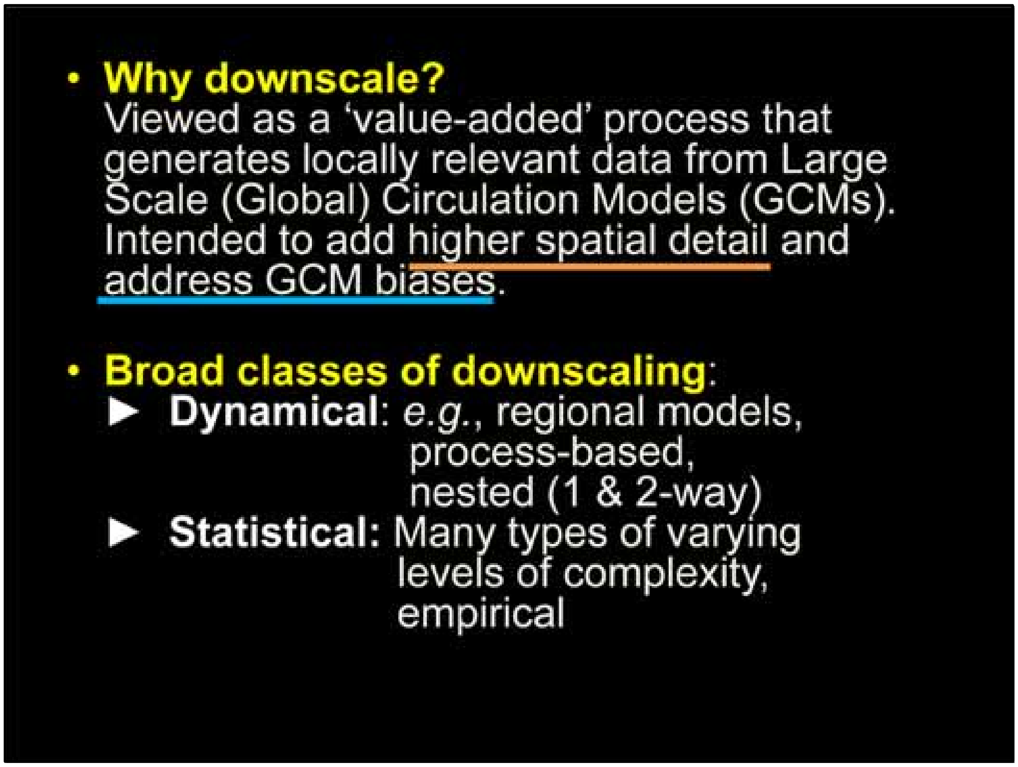
Web page for GFDL's Empirical Statistical Downscaling team: http://www.gfdl.noaa.gov/esd

NOTE: the text contained in the 'notes section' of this document has not been reviewed. It should be considered a rough draft, and should not be quoted. It is provided here in an attempt to capture some of discussion that took place when these slides were shown at the workshop and during Q&A that followed.



Global (or very large spatial scale) dynamical climate models (oceans, atmosphere, +) provide a means to perform physics-based experiments on the vast and interconnected climate system across a range of time scales, though the models obviously are an imperfect representation of the real thing. Comparing observations to a large scale dynamical model's simulation of a reference period typically reveals biases in the model's climatology (not just in means, but in shapes of the PDF, occurrence of extremes, etc.) that may be deemed unacceptable for end-use applications (e.g., climate impacts studies). Additionally, the large scale model's spatial resolution may be too coarse to capture details of interest to stakeholders. For these reasons, the output of large scale climate models is often used as input to 'downscaling' processes that seek to add value by (hopefully) reducing biases and/or adding finer scale spatial detail.



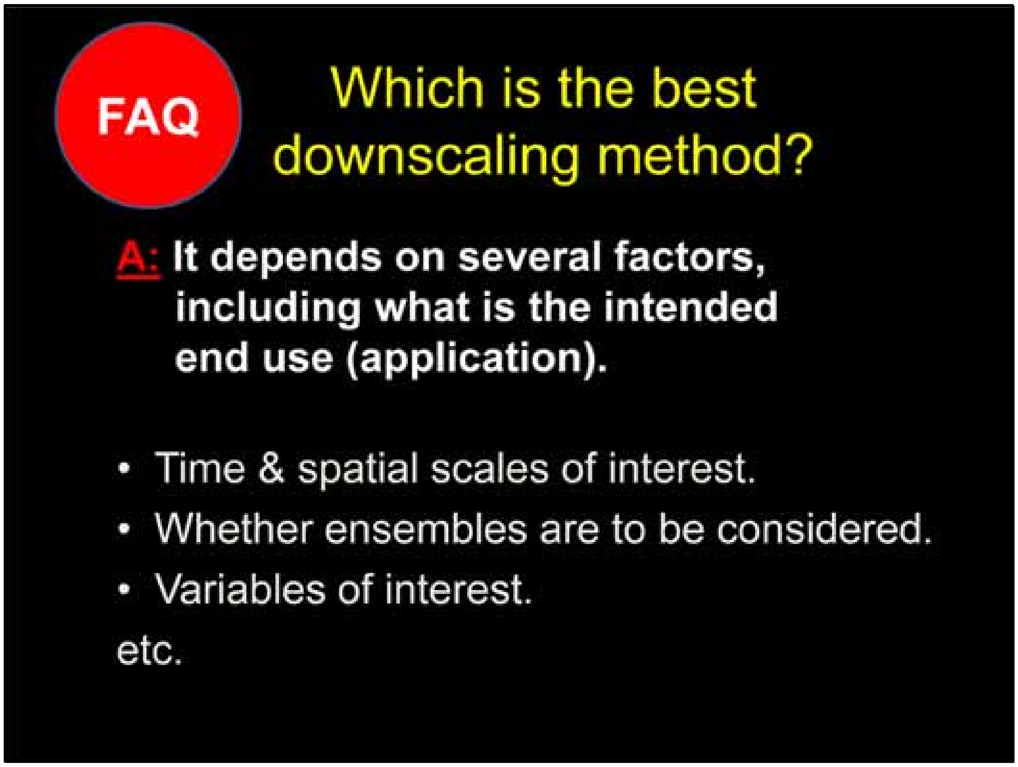
>> **What is Dynamical Downscaling?**
Regional dynamic models (physics-based, ocean and/or atmosphere) span a smaller spatial domain than the large scale model but at higher spatial resolution (i.e., smaller grid boxes). The regional dynamics models are 'forced' at their boundaries by output taken from large scale dynamical models (or reanalysis products). An aim is to resolve important features that were considered sub-grid scale in the large scale model (e.g., bathymetry, clouds).

>> **What is Statistical Downscaling?** (aka Empirical Statistical Downscaling or ESD)
A statistical refinement of dynamical model output, informed by observations. Intended to add higher spatial detail and address GCM biases at low computational cost. Myriad of ESD methods exist, ranging from simple 'delta' methods or bias corrections biased on adding time mean differences, to quantile mapping methods, constructed analogues, and artificial intelligence (machine learning) methods (and others in between).

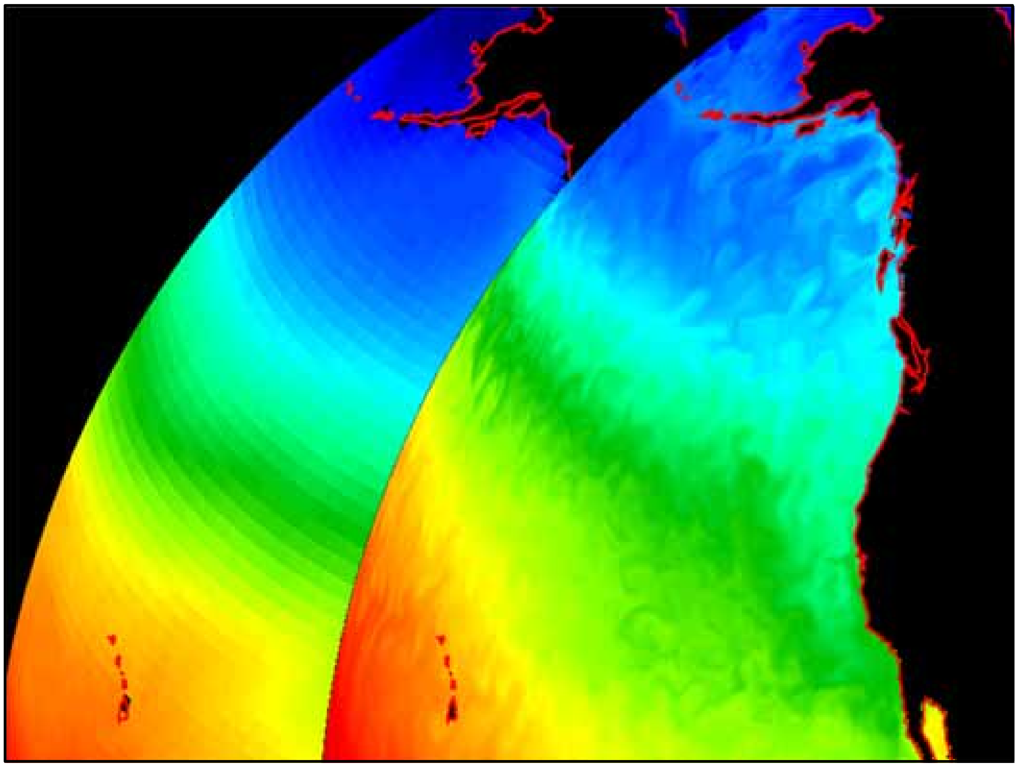
- **Dynamical Downscaling Models:**
  + physically consistent
  - computationally expensive; can require lots of data (GCM or reanalysis) to drive the regional model, inherits driving model characteristics

- **Empirical Statistical Downscaling Methods:**
  + computationally less expensive
  - lacks physical consistency; requires good observational data for 'training'

Each type of downscaling has its pluses and minuses…



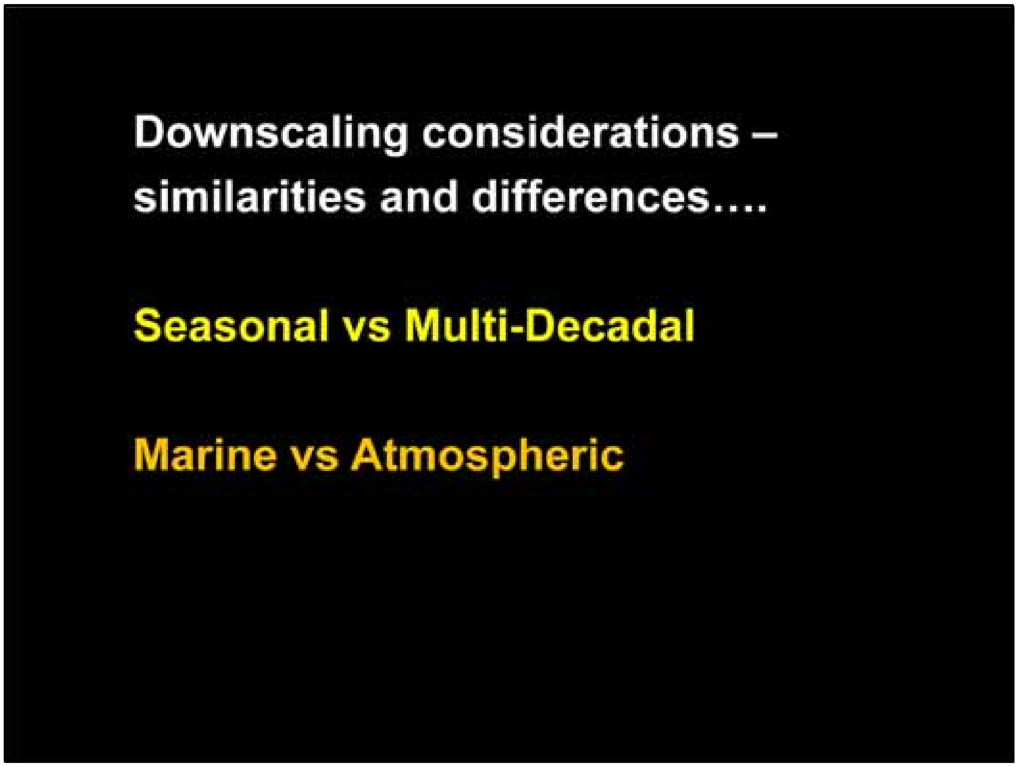
An extremely frequent FAQ asked by climate impacts researchers is *"What is the single best downscaled climate data method or product for my application of interest."*
I usually disappoint the questioner by responding with wishy-washy statement *("I don't know the answer for your particular application -- It depends"*).
Follow up can include a set of questions to see if together we can better determine what the needs are. A method that work OKs for someone interested in how monthly mean July temperatures are projected to change over 50 years may not be appropriate for someone interested in the frequency of extreme wind events at a particular coastal location this coming season.



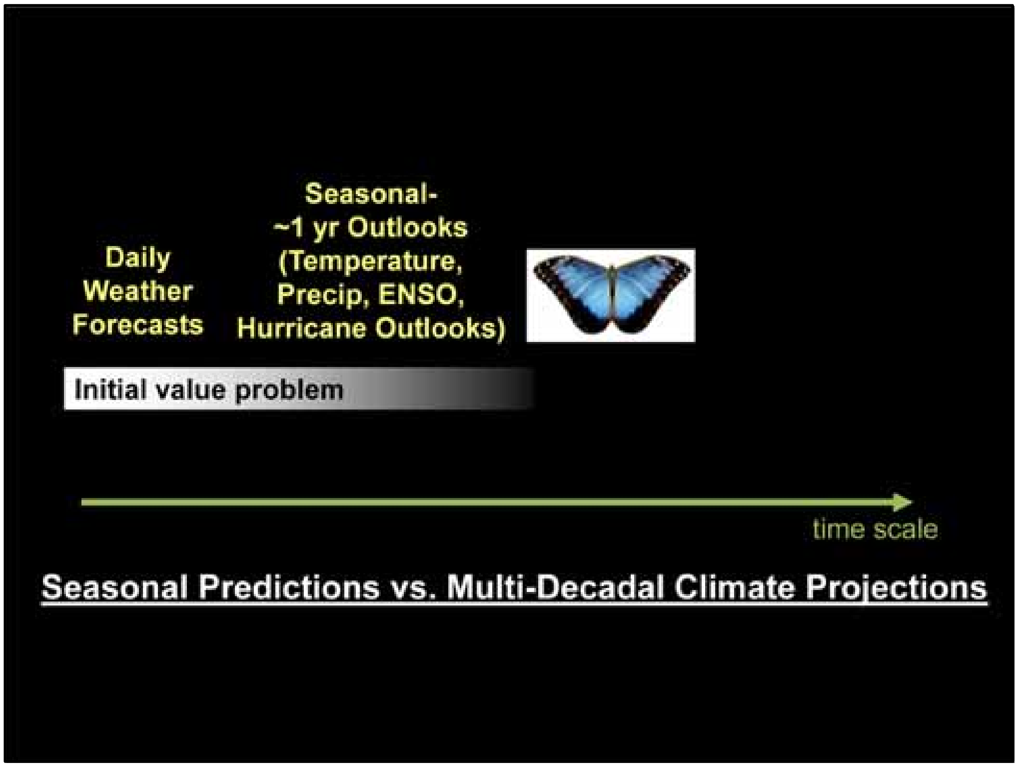
And we ought to acknowledge the allure (siren's song) associated with the appearance of higher spatial detail. The two images here show snapshots of sea surface temperatures simulated by two GFDL models – the model on the left has ocean spatial resolution of about 1 degree latitude & longitude whereas the model on the right has significantly higher spatial resolution leading to the spontaneous appearance of eddies in the model. If I ask most audiences which of these two models is "better", some fraction immediately say the one with the eddies is clearly better -- perhaps because it just looks "more realistic"? However, without additional info, how does one know which of the two models has larger time-mean temperature biases relative to observations, or which does better at simulating the magnitude and timing of the seasonal cycle, or which one does a better job of simulating the frequency, amplitude, and pattern of SST anomalies associated with El Nino events or…? The higher resolution model certainly has the *promise* of yielding more realistic simulations in many regards, but spatial resolution alone doesn't *guarantee* a "better" simulation across the board.

Even a very incomplete review of the scientific literature may reveal that some researchers present downscaling in an extremely flattering and not-too-critical light whereas others express disdain for the way downscaling is used, claiming that it may mask climate model weaknesses but that those weaknesses are nonetheless inherited by the downscaled product.

The purpose of this talk is not to claim that the most appropriate way to view downscaling is closer to one extreme or the other. Rather, the aim is to raise some points and to foster awareness that might promote more informed decisions being made by those who seek to use downscaled information in their work.



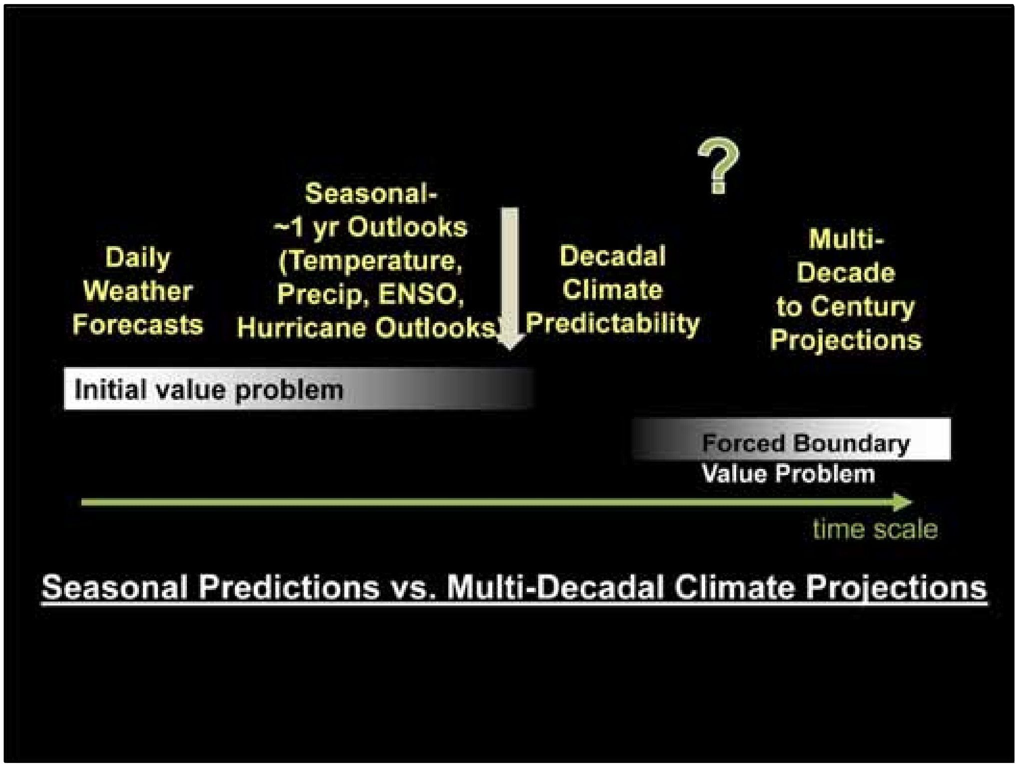
Though the GFDL statistical downscaling team's experiences to date have focused primarily on multi-decadal time scales and surface weather variables (e.g., daily temperatures & precipitation), our belief is that many of the concepts and concerns are applicable across multiple time scales and have relevance to marine applications. Still, there are some key differences in the nature of the problems being addressed that one should also consider…



Instead of simply categorizing things into "weather" and "climate" let's look at things in a slightly different way. Let's think about what it would take to make a skillful forecast or projection for different types of weather and climate questions in the following framework. The shorter term problems can be considered to be "initial value problems". In other words, if we assume (hypothetically) that we have an almost perfect understanding of the way the system works (e.g. via a dynamical model, a statistical model, our own experiences and intuition) then the skill in the forecast will depend upon how well we can specify the "initial value" – the starting point – the initialization state. The better the initialization captures the true state of the atmosphere-ocean system, the better the forecast of how the system evolves in time from that starting point will be… up to a point.

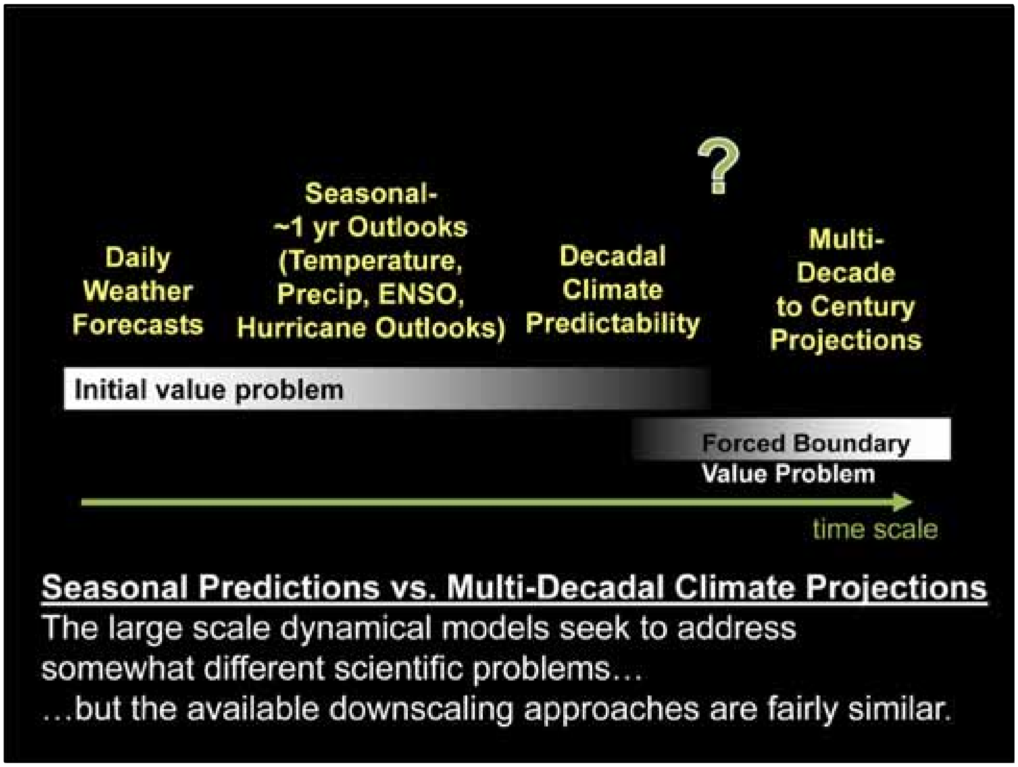
There's a limit to the predictability. Because the system is somewhat chaotic, we don't expect that we will ever be able to make skillful day–to-day forecasts a month in advance regardless of how well we understand the physics of the system and how well we measure the current conditions. By "chaotic" we mean that very, very, small differences in the initial state – differences too small for us to hope to measure – lead to the system evolving in divergent ways as time progresses. Over time, those miniscule differences in the initial state will grow and propagate, leading to two systems that at the start were almost identical to evolve in difference ways so that they will no longer resemble on another.

This chaotic element – or sensitivity to initial conditions – was referred to the "Butterfly Effect" described by Ed Lorenz [see http://www.technologyreview.com/article/422809/when-the-butterfly-effect-took-flight/]

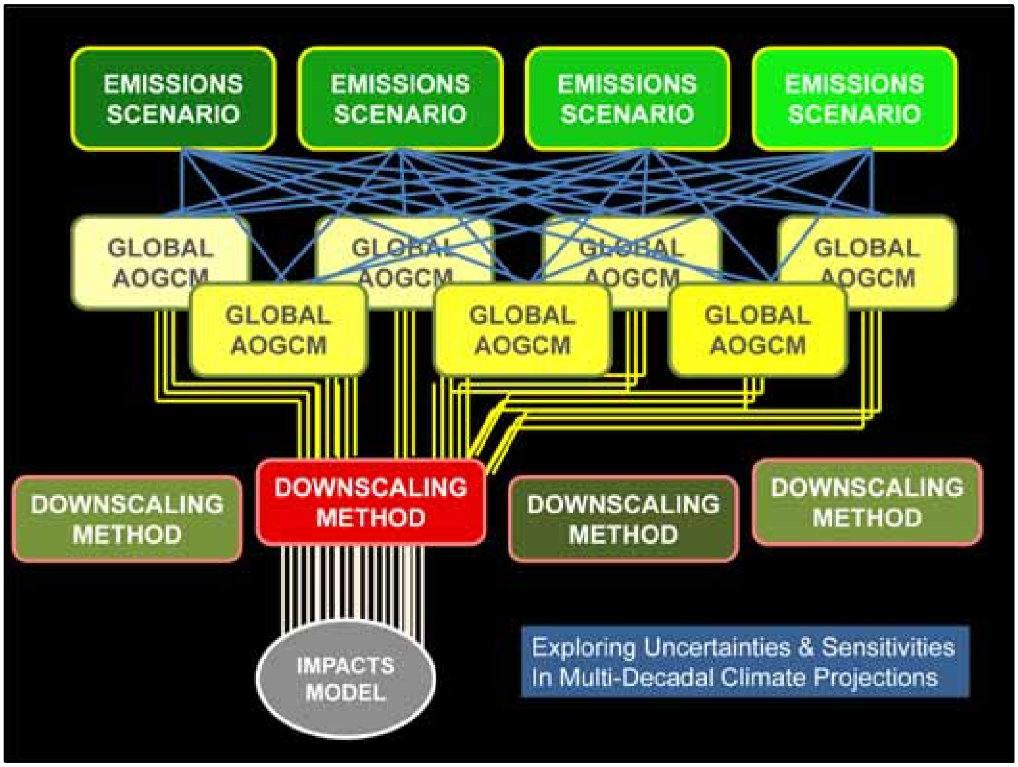


Q: Why do we think we can make meaningful 100 year climate projections when we can't forecast the day-to-day weather a month from now?
A: Because we're asking different scientific questions. A multi-decade to century time scale climate projection is a "boundary value" problem – not an "initial value problem". We're not trying to predict the "internal variability" of the system (i.e., the unforced relatively short-term wiggles in the system that arise spontaneously and not as the result of external forcings). Rather, we are attempting to determine how the statistics of the climate (e.g., means, variability, skewness of distributions, etc.) over time may change in response to changes in external forcings.
So, we are not trying to predict whether the specific year 2085 will experience El Nino, La Nina, or neutral conditions in the tropical Pacific. However, questions of how the character (statistics) of ENSO variations may change by 2085 compared to today in response to external forcings does fall under the umbrella of DecCen Climate Projections (i.e., might the amplitude, frequency, or pattern of tropical SST variations in the late 21st century be significantly different that they were during the late 20th century is a valid, if not resolved question).

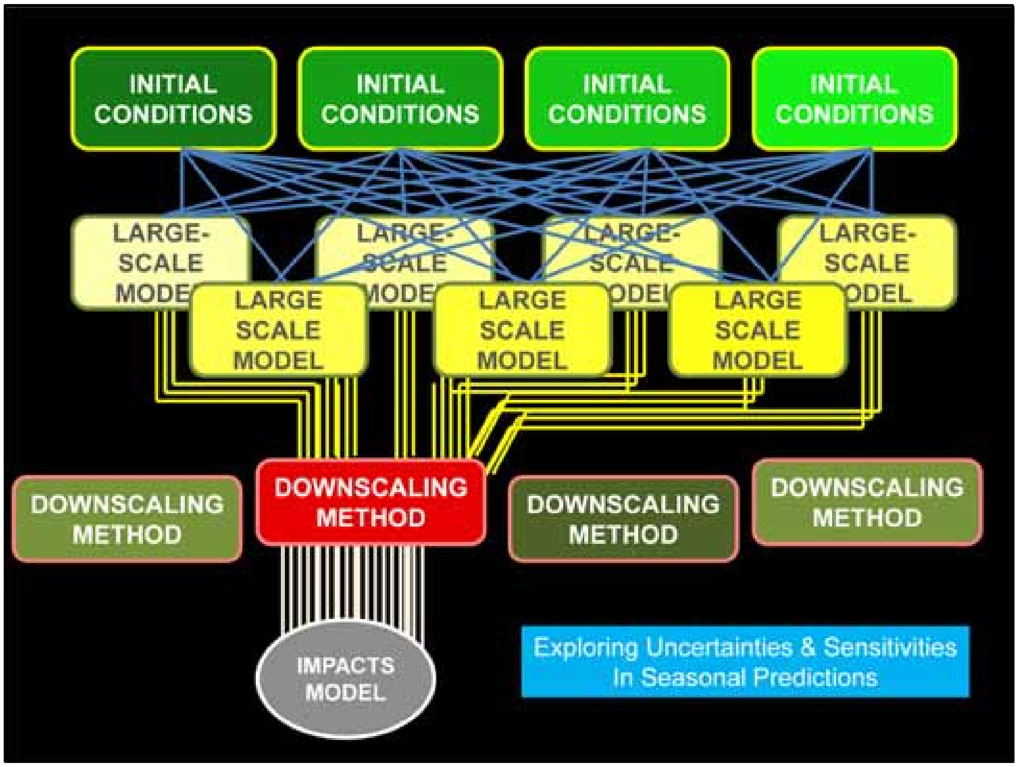
For related info, see "***Weather Prediction, Climate Prediction. What's the Diff?"*** by Bill Chameides on the PopSci web site…
http://www.popsci.com/environment/article/2009-03/weather-prediction-climate-prediction-what's-diff



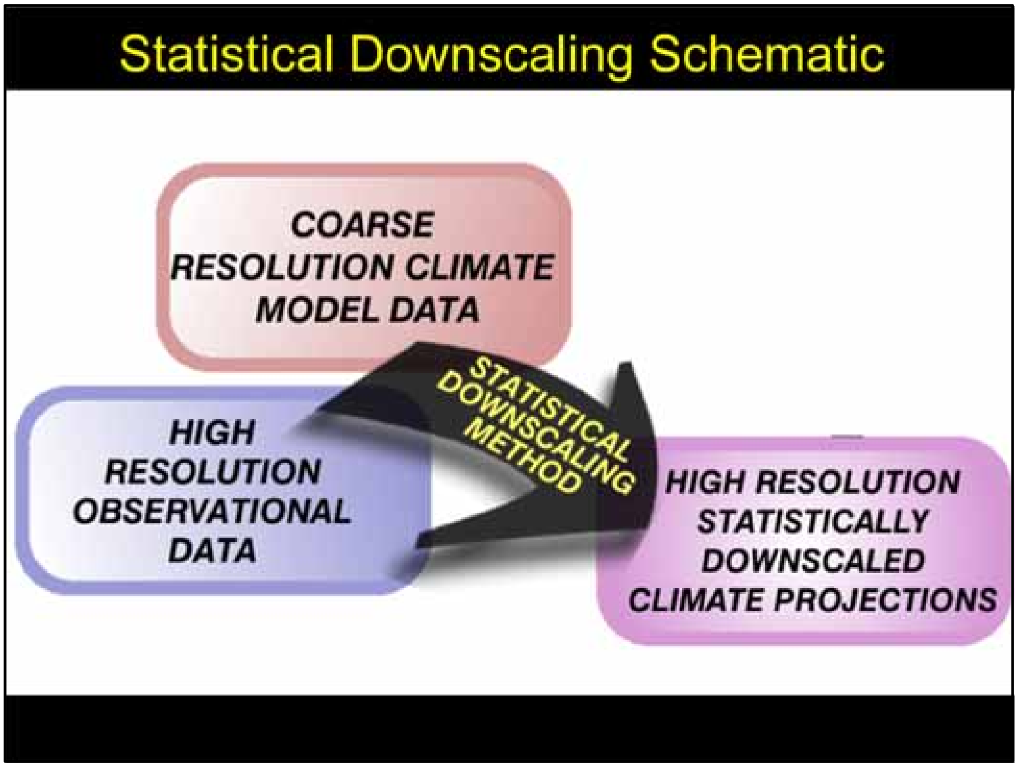
Note: when we say “external forcings” we are referring to environmental factors that when added or removed change the flow of energy (especially radiative energy) through the climate system. Carbon dioxide and methane are examples of forcing agents that absorb and re-emit infra-red radiation, thereby affecting the flow of energy, with a net effect of warming the surface of the planet. Cut down a forest and replace it with pasture and you change the albedo – also a radiative forcing. Adding soot tends to warm the surface. Sulfate aerosols tend to cool the surface. Volcanic aerosols cool the surface and warm the stratosphere for a few years. The Sun’s output can change slightly over time, etc. These are all considered external forcings… forcings to which the climate system responds.



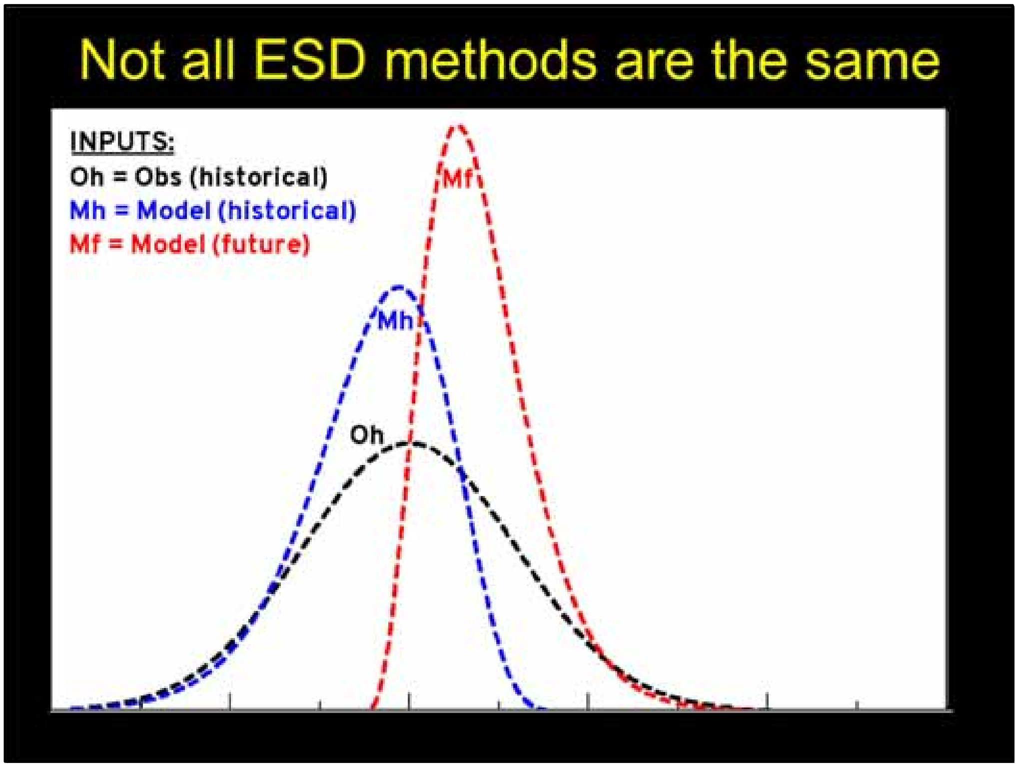
There's not just one emissions scenario, and not just one global atmosphere-ocean global climate model (AOGCM), nor just one way to downscale.
It is common to see climate change studies in which multiple emissions scenarios and multiple GCMs are studied, with the range or 'envelope' of the different results taken as being somewhat indicative of the uncertainty of future projections. However, many of those studies process the GCM results using a single downscaling method, in effect neglecting that the downscaling process itself introduces uncertainties (evident in that different downscaling processes will yield somewhat different data products).



Similarly, sets of seasonal forecasts may be developed using different large scale dynamical models and different initial conditions in order to capture some of the uncertainty… but, as was the case for the multi-decadal projections depicted on the previous slide, piping seasonal forecast output through a single downscaling method also fails to acknowledge the downscaling step itself introduces uncertainties at the same time it attempts to add value by addressing large scale model biases and providing finer spatial detail.



This schematic reminds us that the statistical downscaling process typically involves use of observation-based data taken as “truth”, be it a gridded product or station data (bubble labeled ‘high resolution observational data’) -- and a set of dynamical model results representative of the same period for which there are observations (bubble labeled ‘coarse resolution climate model data’). The black arrow represents the process by which statistical relationships (transfer equations) between the model and truth are determined and subsequently applied to generate the ‘refined, value added’ statistical downscaled product used as input to many climate impacts applications. A wide range of statistical downscaling methods exist... There are different classes of methods and within different classes, there can be many variants.



The next few slides present some figures developed by GFDL statistical downscaling team to illustrate how a few different statistical downscaling techniques can yield somewhat different results.

On this slide, 3 dashed curves represent PDFs of the three types of data sets a researcher has on hand when considering climate change projections. We can think of these as some sort of temperature-based variable, where…

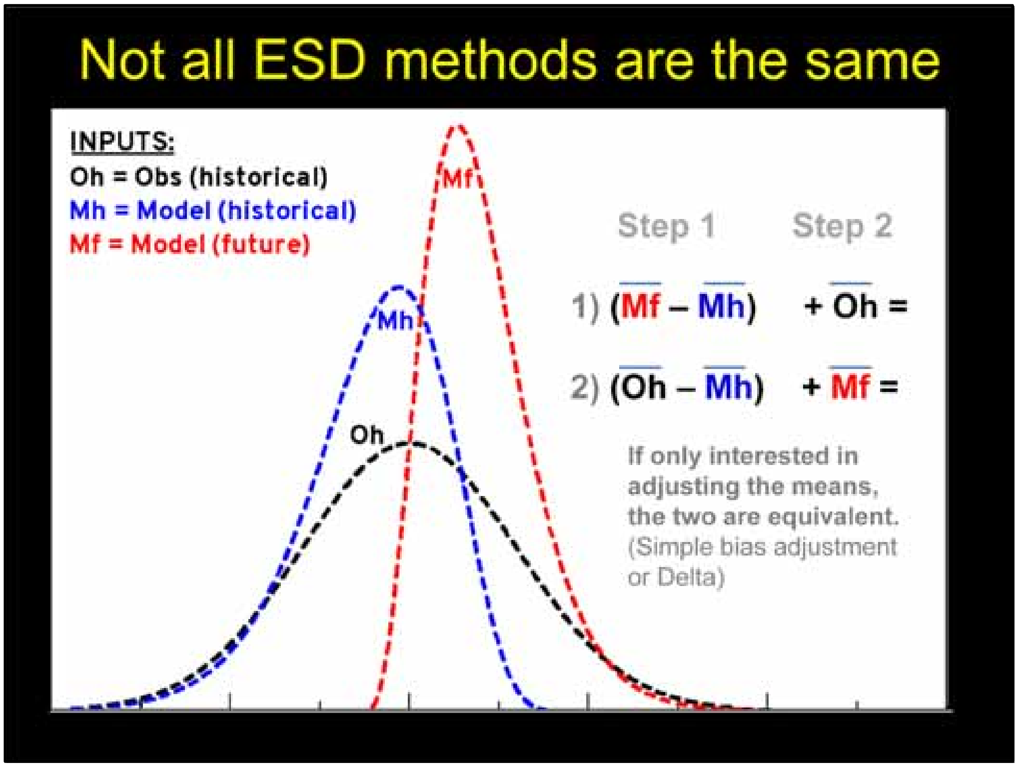
Oh = Observations from the Historical period.

Mh = climate Model from the Historical period.

Mf = climate Model from a Future period.

We note that, compared to the Observations (Oh), the Model (Mh) is biased toward somewhat cooler average temperatures, with most of the bias associated with the model under-simulating the warm tail of the distribution. Also, the model-simulated climate change signal (Mf vs Mh) is characterized by both mean warming and reduced Future variance in the form of a steeper, shorter cool tail of the Model's Future PDF relative to the Model's Historical simulation.

Given these 3 curves, what should the PDF of the statistical downscaled estimated for the Future look like???

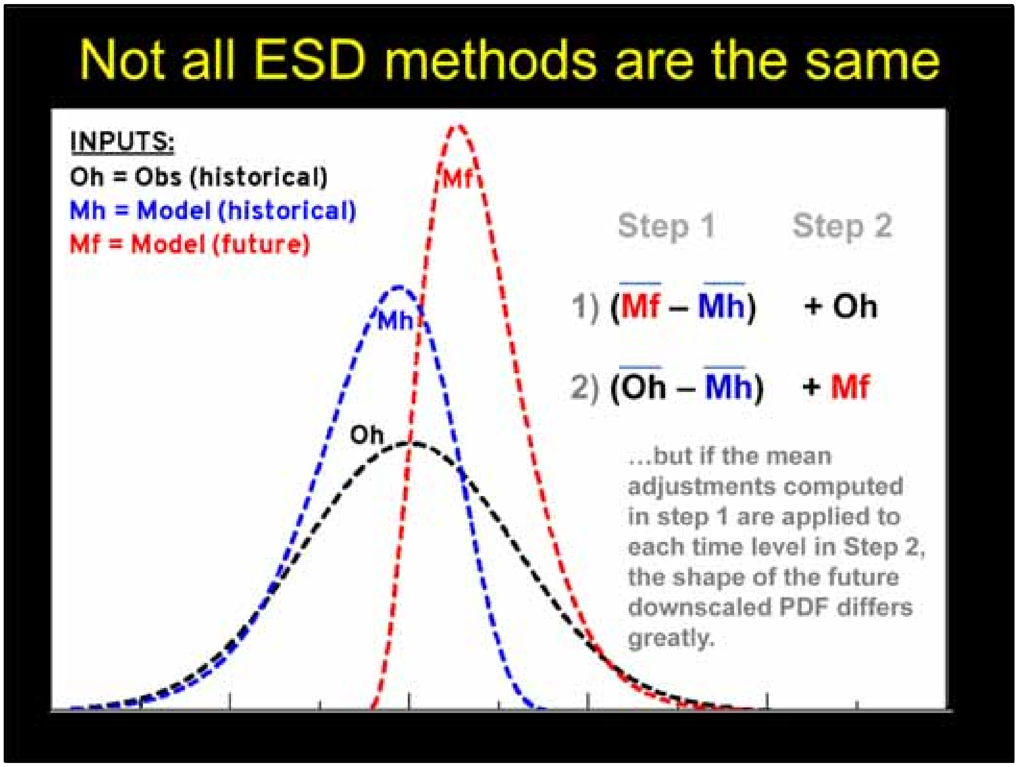


Some simple Bias Correction or Delta methods work by comparing Means of two of the three available distributions and adding the resultant constant offset to the third in order to produce a 'refined' Future estimate.

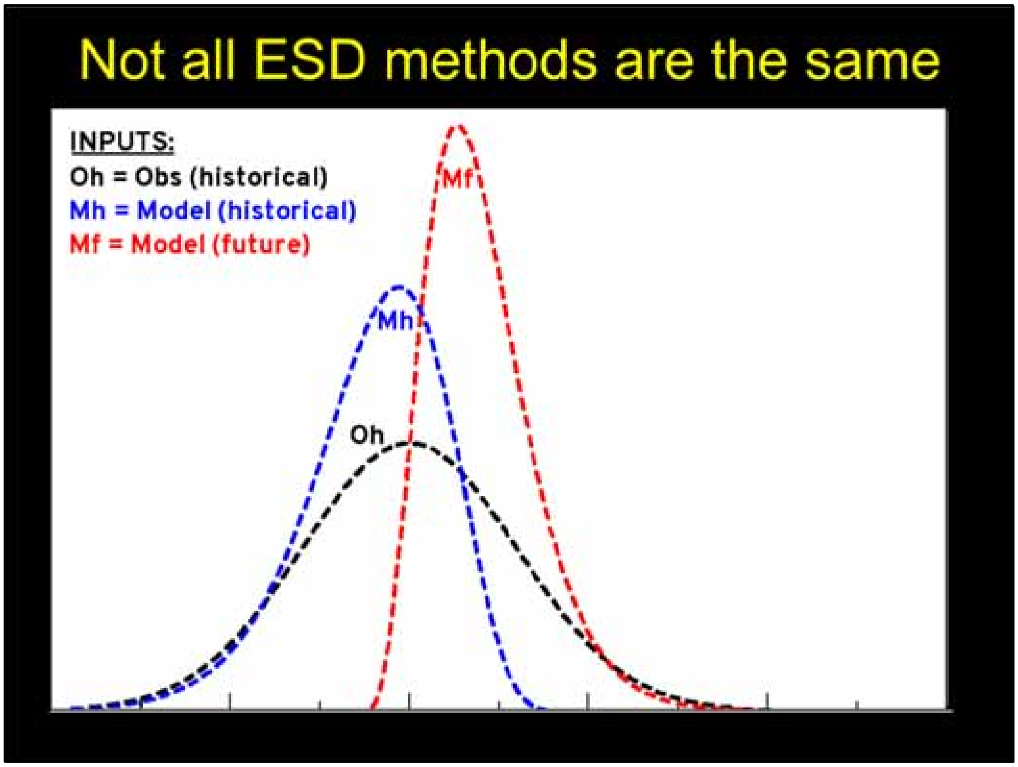
For example, a 'Delta' approach (1) computes the model simulated mean climate change response and adds it to the Observations.

Alternatively, a 'Bias Correction' approach (2) could determine to what extent the time mean modeled historical (Mh) data differs from Observations from the same time period (in this case, the model has a cold bias) and adjust the Modeled Future simulation by that mean difference, in order to account for the bias.

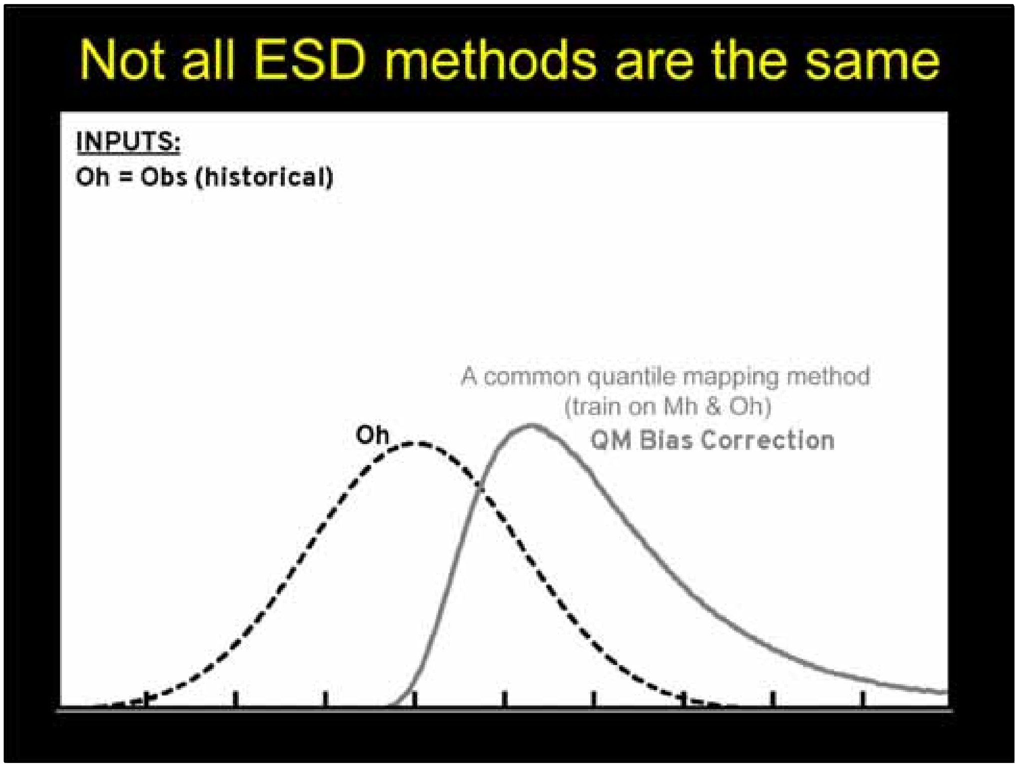
If you are only interested in the means of the refined Future values, then the results produced by methods (1) and (2) are the same. However…



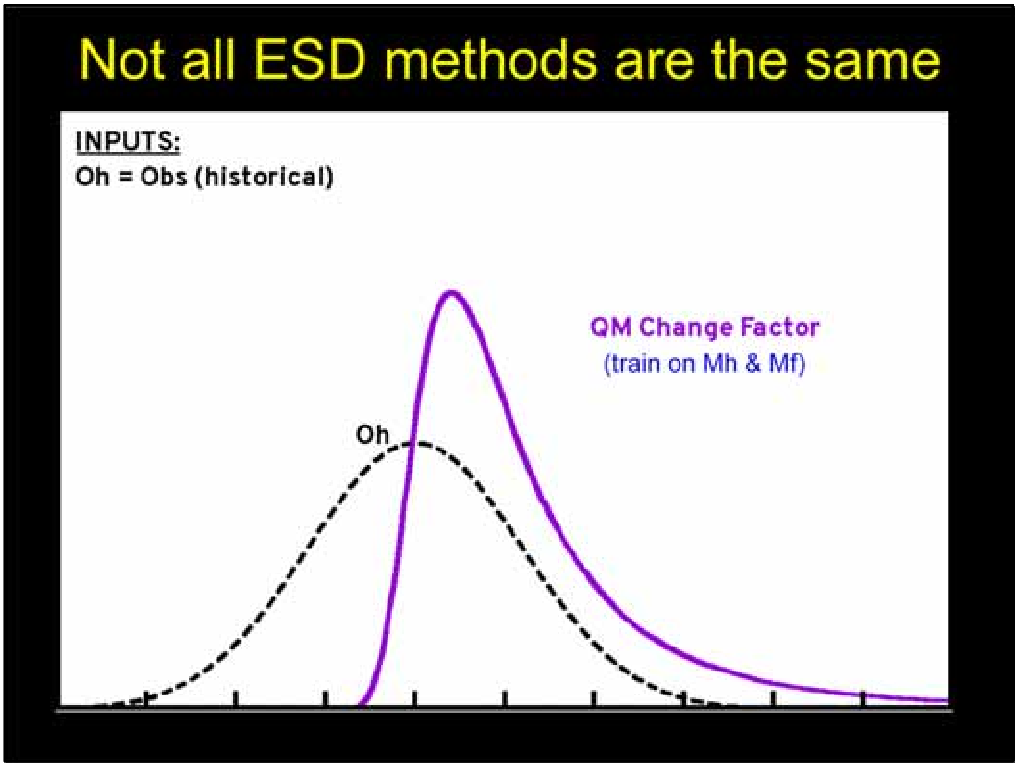
…The shapes of the refined Future PDFs produced via methods (1) and (2) are not the same, although the means of the two would be the same.
The Delta approach (1) yields a future PDF [not shown] having the same shape as the Oh curve whereas the Bias Correction approach's PDF [not shown] (2) has the exact same shape as the Mf curve.



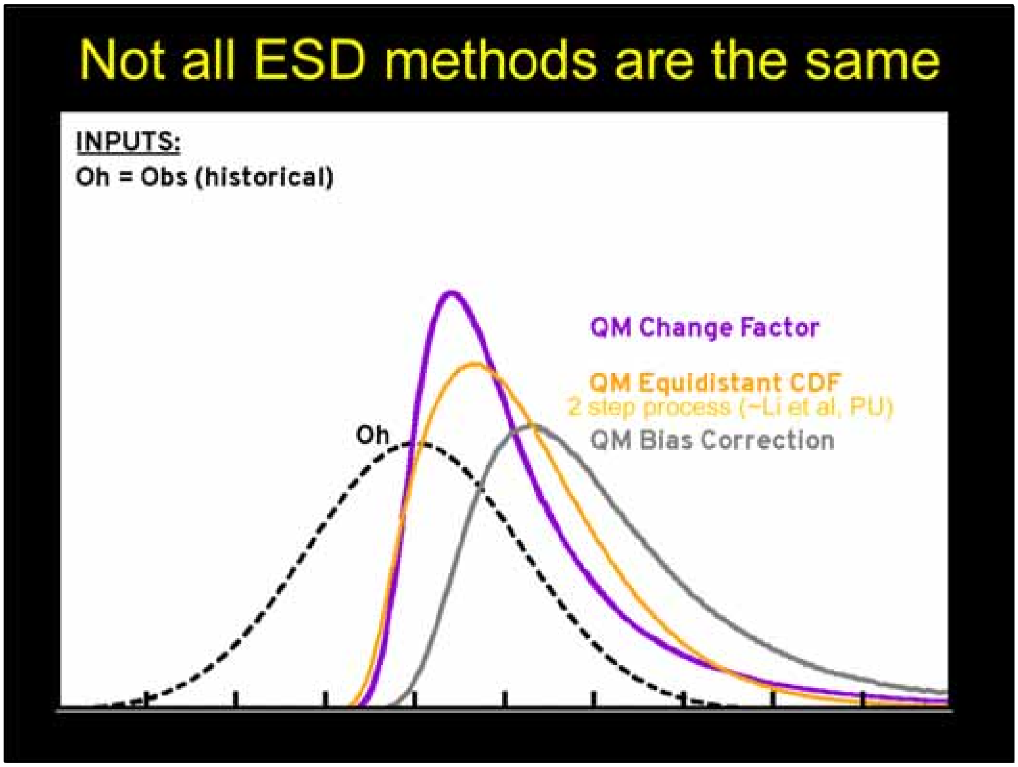
The previous 2 slides discussed how the PDFs of 'refined' future projections could differ when simple, constant offsets were applied. A step up in complexity could be to not simply adjust all values by a constant offset, but to rather consider the different parts of the PDFs when making refinements (so one might adjust the cool tail by a different amount than the middle of the distribution and the warm tail by a different amount, too). Quantile Mapping methods (and related 'distributional techniques) take this general approach, but many different implementations exist – each of which employs somewhat different statistical techniques to compare the distributions and generate the downscaled future projection. So, presented with the same three data sets, Oh, Mh, & Mf…



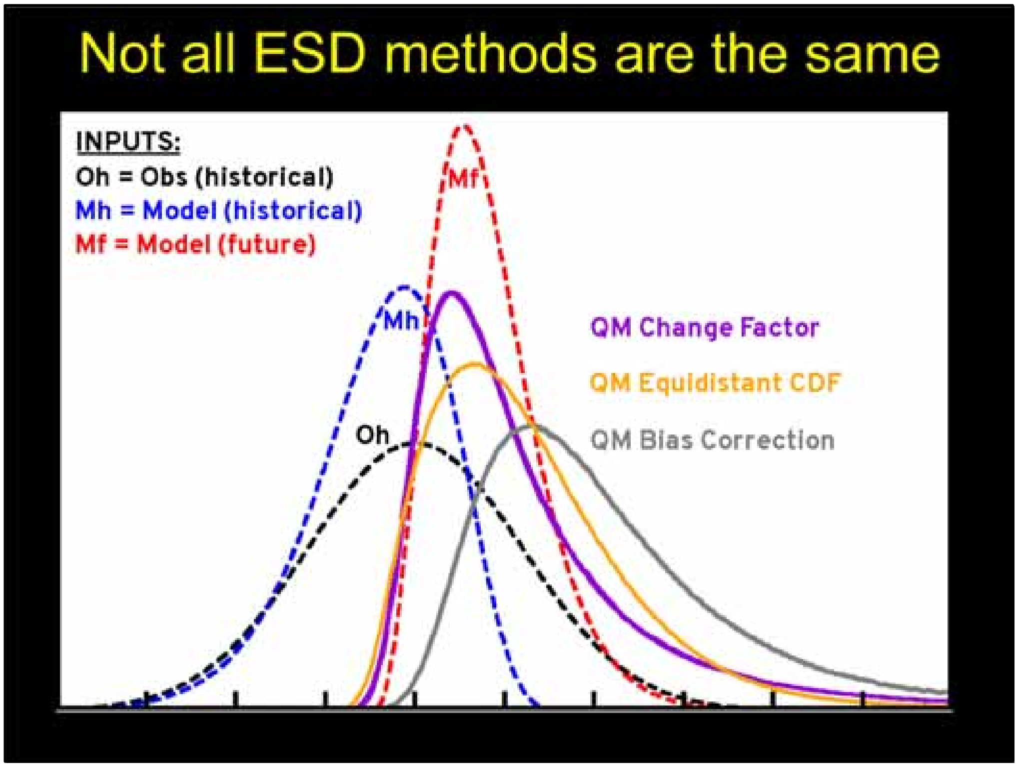
A stripped-down, no-frills version of a Quantile Mapping Bias Correction produces this PDF as its downscaled future projection.



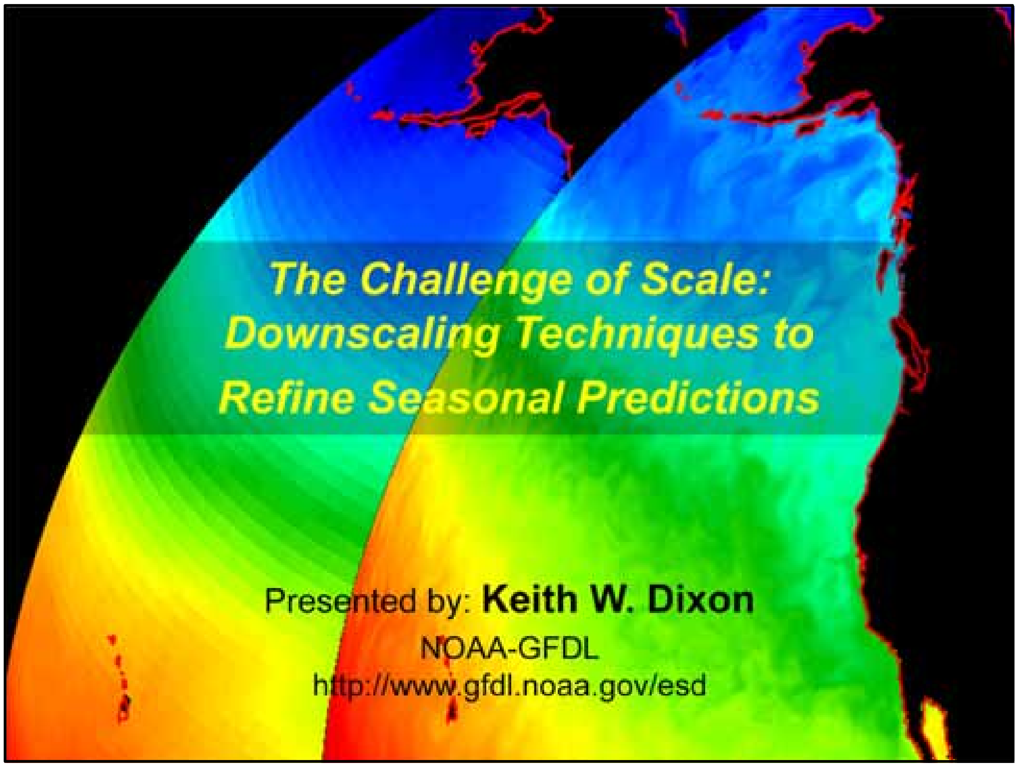
And a Quantile Mapping Change Factor type of method yields this PDF for its downscaled future projection…



And another method (after the Equidistant CDF method of Li et al) yields a PDF that lies between the previous two.



So, the note of caution being expressed here is that different statistical downscaling methods are going to produce somewhat different results (even methods in the same general class can differ in important ways) – something that we believe users of downscaled data sets should at least be aware of, so that they may make better-informed decisions when selecting climate projections for use in their applications.



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Links to items referenced within this presentation & during the workshop Q&A session include:

Barsugli JJ, et al (2013) The Practitioner's Dilemma: How to Assess the Credibility of Downscaled Climate Projections. Eos, Trans Amer Geophys Union 94:424–425. doi: 10.1002/2013EO460005
http://onlinelibrary.wiley.com/doi/10.1002/2013EO460005/abstract

The GFDL ESD Team's "Perfect Model" experimental design:
http://gfdl.noaa.gov/esd_eval_stationarity_pg1

NCPP home page (National Climate Predictions & Projections Platform):
http://earthsystemcog.org/projects/ncpp/
GFDL linkage: https://www.earthsystemcog.org/projects/gfdl-perfectmodel/