The importance of natural internal climate variability in climate prediction & communicating near-term forecasts to the public and policymakers

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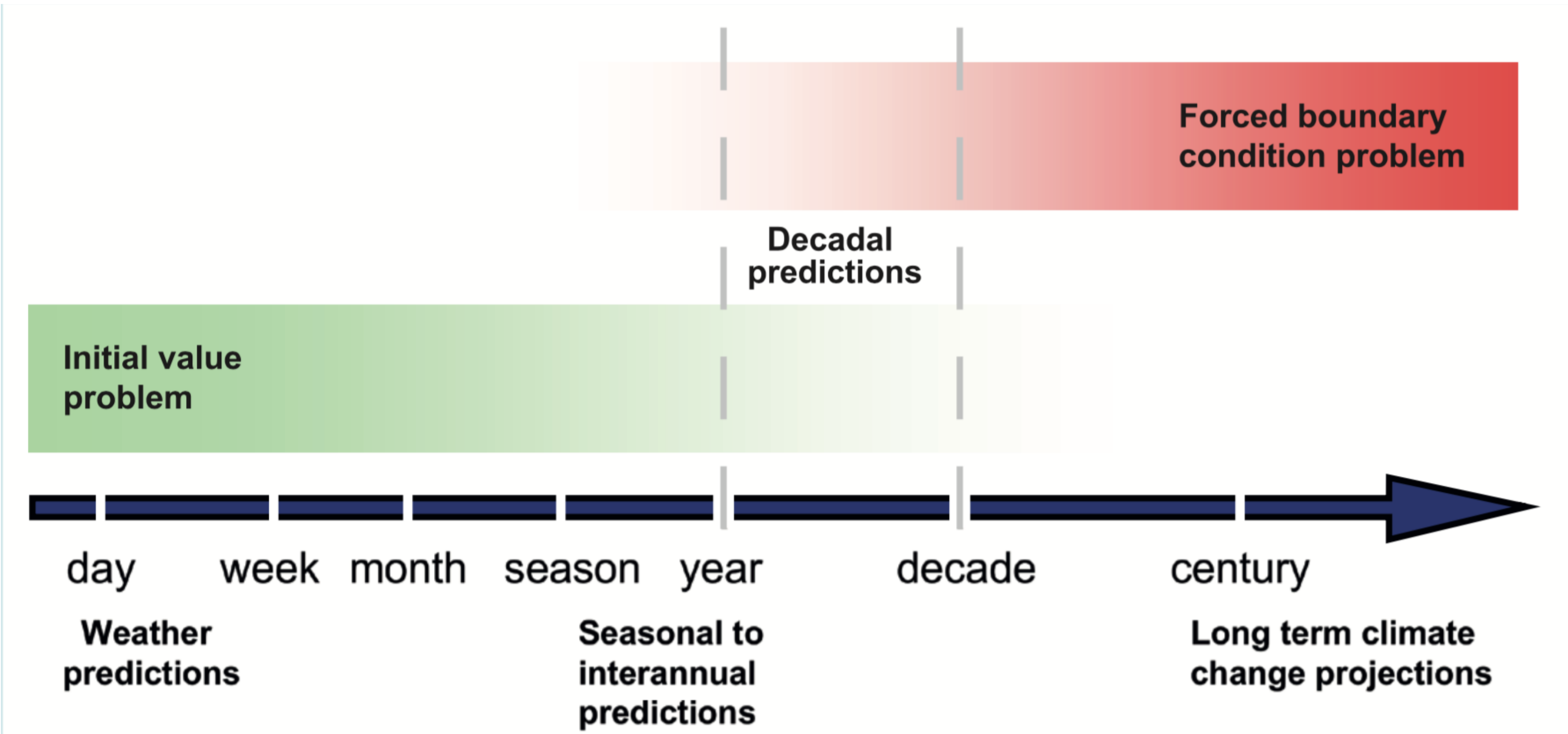
Discussion based on Deser et al and Hawkins and Sutton papers

What is a "near-term" forecast?

- Climate projections of changes due to increased greenhouse gases go out to the end of the 21st century!!
- Quick show of hands: who is going to be here then?
- Would be useful to know something about the next 5, 10, 20+ years too.
  - Especially useful for adaptation/mitigation
- What we want is a "near-term" forecast

Climate predictions and projections



See Kirtman et al, 2013: **Near-term Climate Change: Projections and Predictability** (IPCC chapter 11)

Some key points about climate

- Climate anomalies have large scale (hemispheric to global) patterns called *teleconnections*
- Climate signals can be small compared to natural weather variability, which often looks like (red) noise
- Climate forecasts involve predicting *changes* in the odds of different weather events (probability distribution)
- Climate forecasts require an *ensemble* of individual forecasts, each run with a small change in atmospheric initial conditions
  - Because of chaos (butterfly effect), each forecast will evolve differently
  - Each forecast (if model is perfect) is equally likely, but only one will actually occur

What is climate?

Climate is what we expect. Weather is what we get. – Ed Lorenz

- Climate is the average
- Climate is a statistical description of weather (more general)
- Climate is what can be predicted after about *two weeks*
  - “Butterfly effect” (chaos) limits day-to-day prediction
  - Climate *predictability* comes from slow processes (esp. ocean and land)
- Climate is what influences the weather we get

Weather vs. climate in the atmosphere

500-mb geopotential height* maps, 12 hours apart

Note how fronts ("short wave troughs"; dashed lines) move, while climate pattern ("long wave") is fixed

*Altitude of 500-mb pressure surface, or mid-point of atmospheric mass

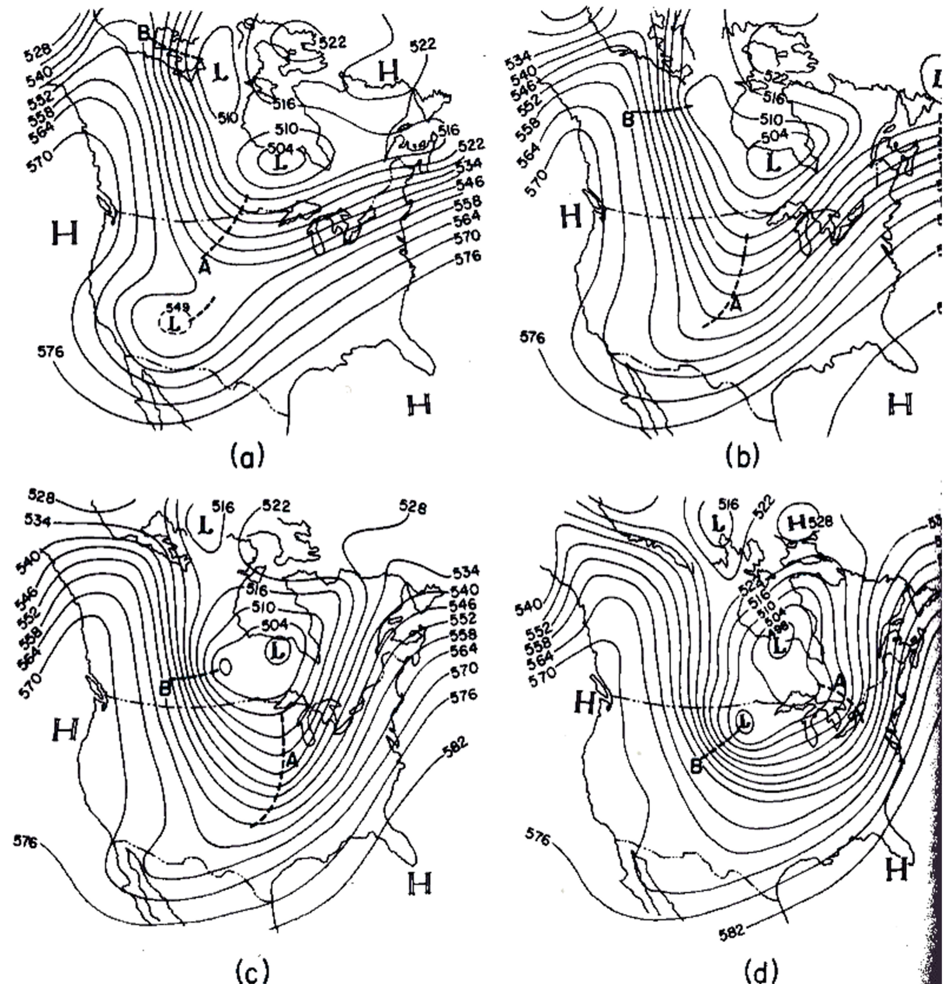
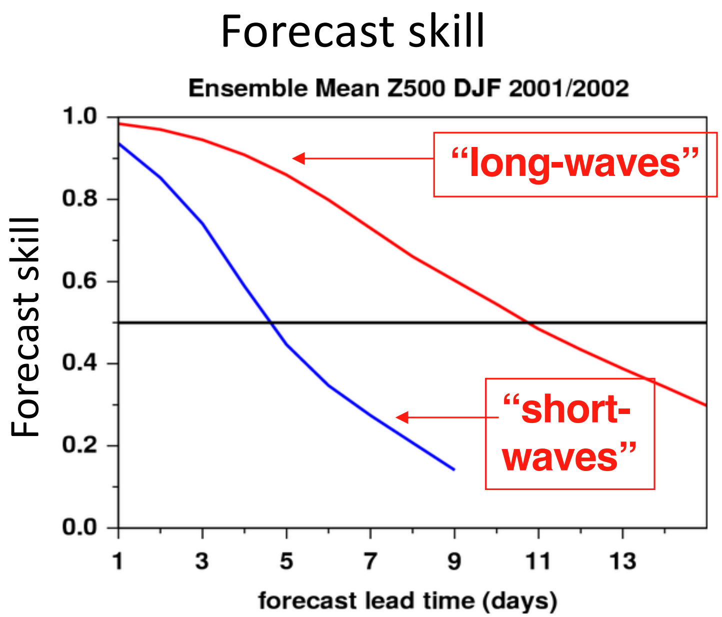


Fig. 3.2 The distribution of geopotential height on the 500-mb surface at 12-h intervals beginning at 00 GCT 19 November 1964 in (a) and ending at 12 GCT 20 November 1964 in (d). Contours are labeled in tens of meters.

Daily vs. "climate" forecast skill



- Most skill is lost for "short-waves" for a 5-day forecast.
- "long-waves" skillful well into week 2.
- Must infer *statistics* of "short-waves" from "long-waves".

Forecast: predict the long-waves (climate) that steer the short-waves (weather)

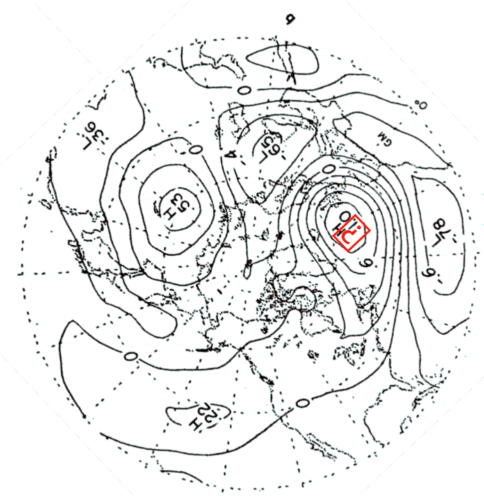
Teleconnections: the alphabet of climate

Teleconnections represent planetary wave-like climate anomalies

Figure: “one-point correlation maps” of monthly-averaged wintertime 500 mb geopotential heights

“Pacific North-America (PNA)”

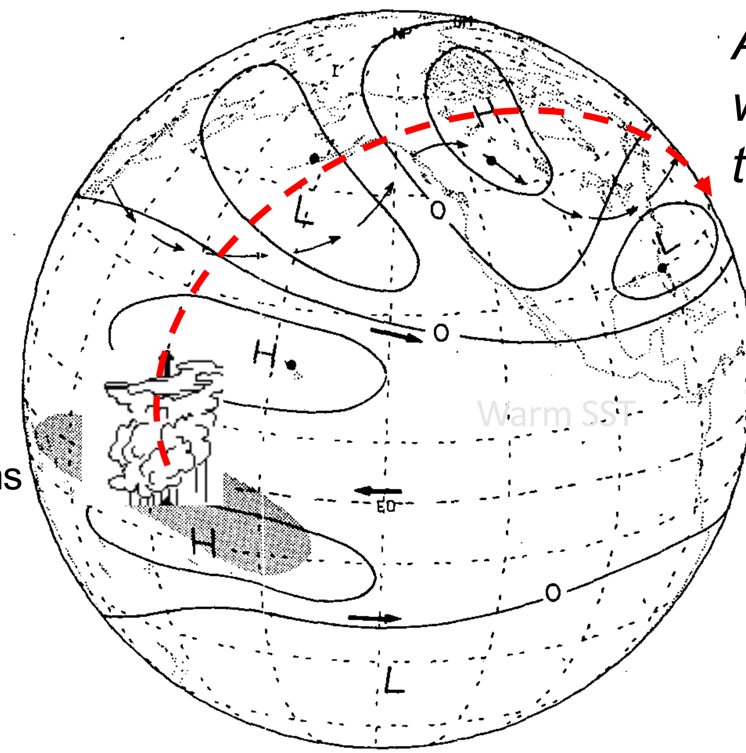
“North Atlantic Oscillation (NAO)”

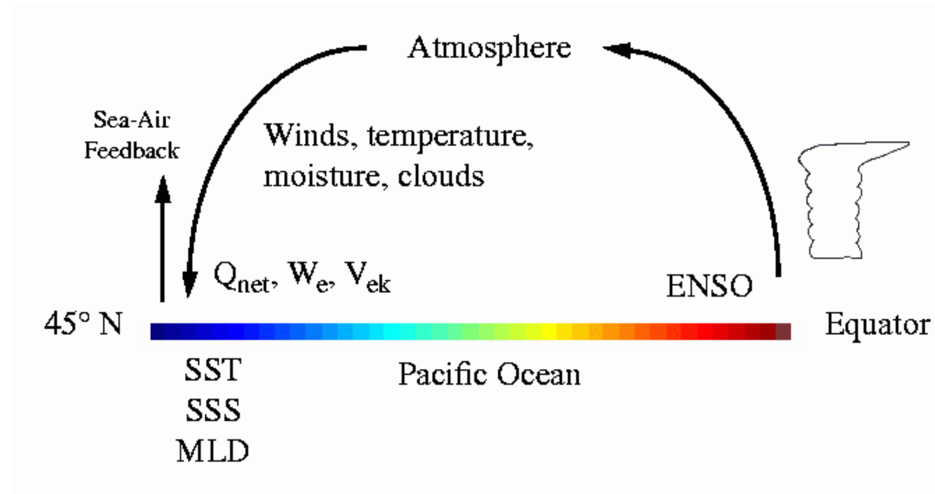


El Niño-Southern Oscillation (ENSO) forces a teleconnection emanating from Tropical Pacific to encircle the globe: impacts climate and weather worldwide

Atmospheric Rossby wave forced by tropical heating

Latent heat release in thunderstorms



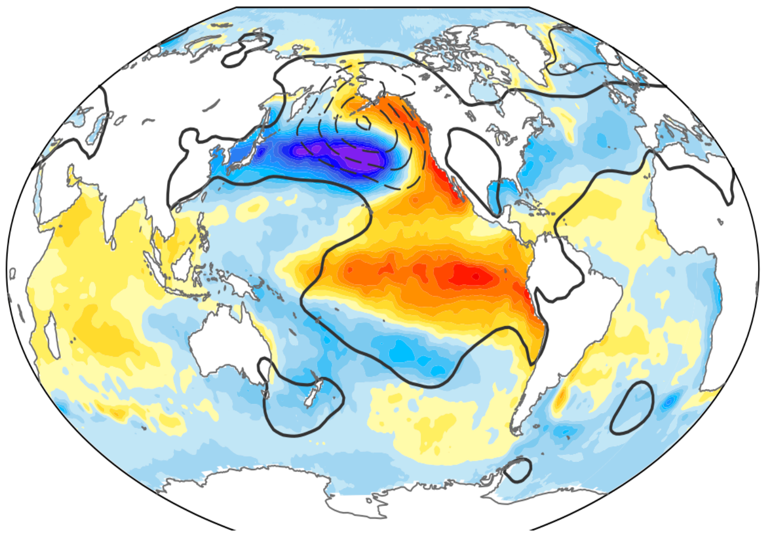


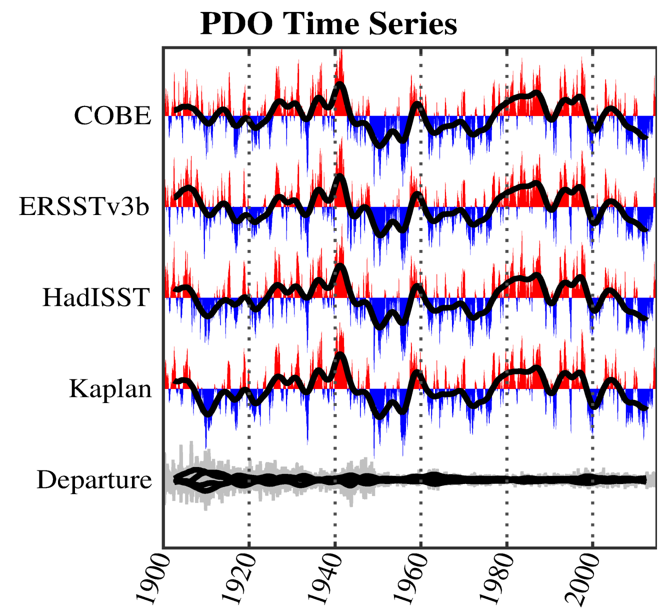
“Atmospheric bridge”

Pacific Decadal Oscillation (PDO)

Shading: sea surface temperature (SST) anomaly

Contours: sea level pressure (SLP) anomaly





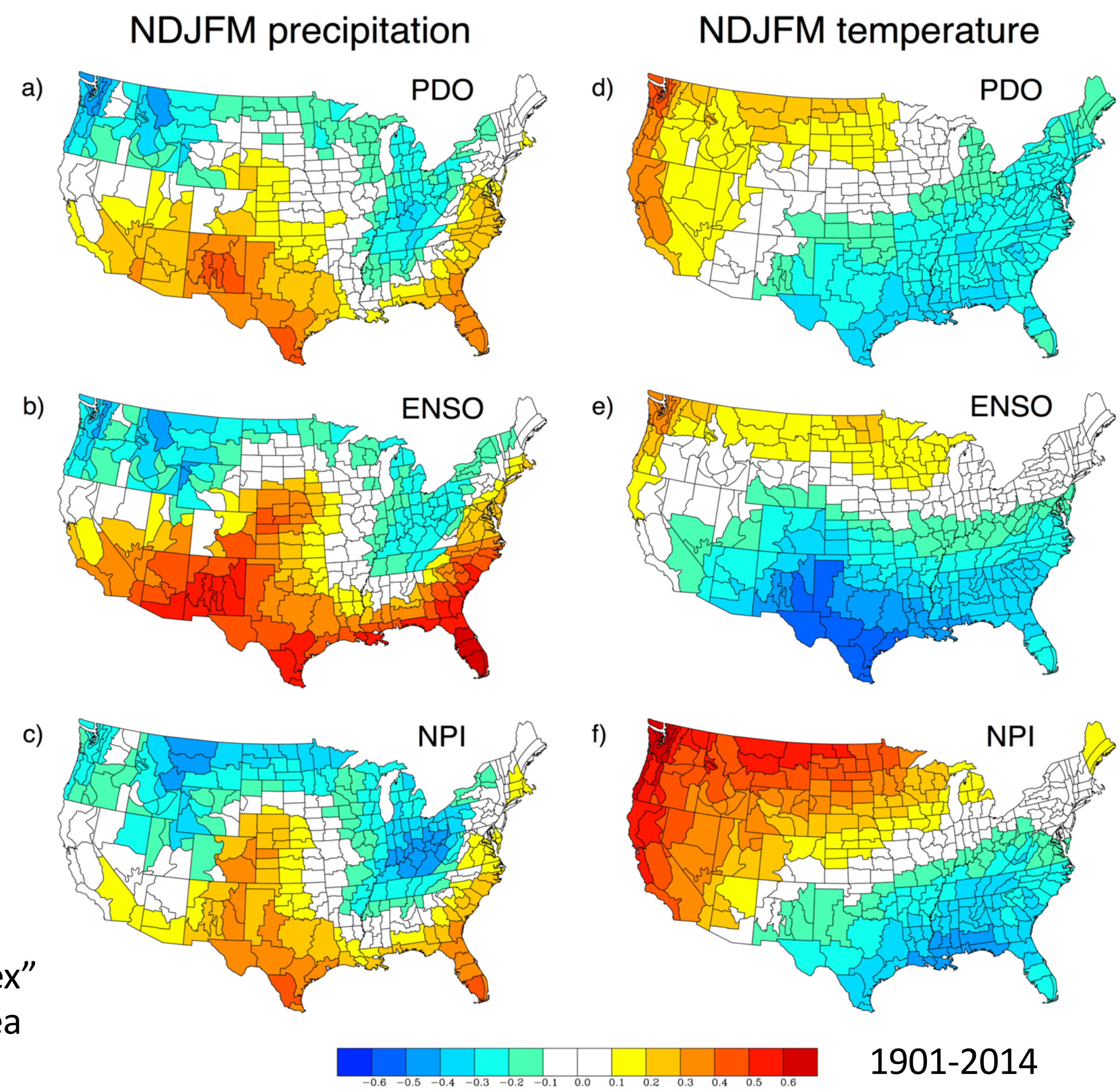
- Leading pattern of monthly SST variability worldwide
- Associated with climate, ecosystem and hydrologic fluctuations, possibly even global temperature "hiatus"

- AKA: "ENSO-like decadal variability"
- Due to a combination of different processes, including ENSO teleconnections changing weather over the North Pacific, whose effects are integrated by ocean there

ENSO and PDO climate impacts

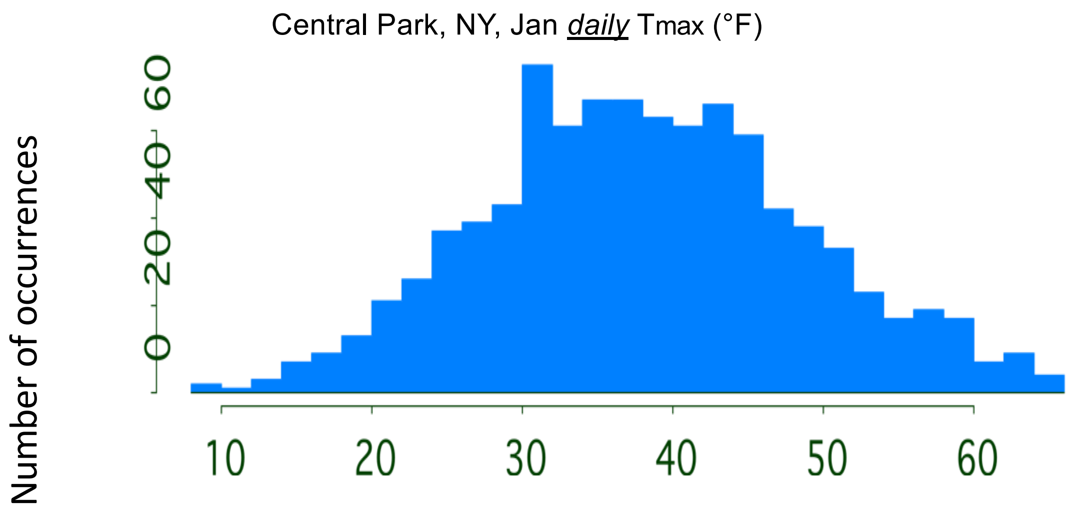
Note that these correlations are still not that high, and this is for *seasonal* averages

And ENSO is the most predictable climate signal!



NPI = "North Pacific Index"
= Aleutian low (sea level pressure)

Climate is a statistical description of weather

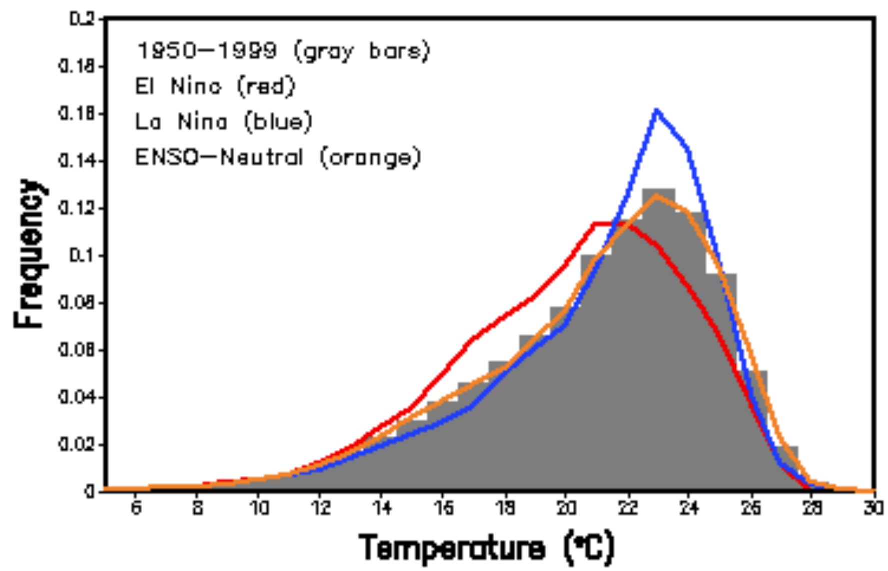


Use this to determine *probabilities* of different max temperatures

Climate forecast: changing the odds of weather

How does El Niño change the probability of daily maximum temperatures in Miami?

Miami FL, Jan-Mar *daily* Tmax (°F)



We can’t make just one climate forecast

- We’re trying to predict a small change in signal compared to a large amount of “noise” (internal weather variability)
- We’re trying to predict a *change* in a distribution
- So we need to make *many* forecasts, called an “ensemble”

But now…

- We make *many* forecasts, but only *one* of them will actually occur
- (At best: models are imperfect)
- This leaves us with a problem of **predictability**, based on
  - How big is the *signal* we are trying to predict?
  - How much *noise* is there?
- Even if our model is perfect, there is still irreducible uncertainty due to internal variability

Uncertainty in seasonal El Niño/La Niña forecasts

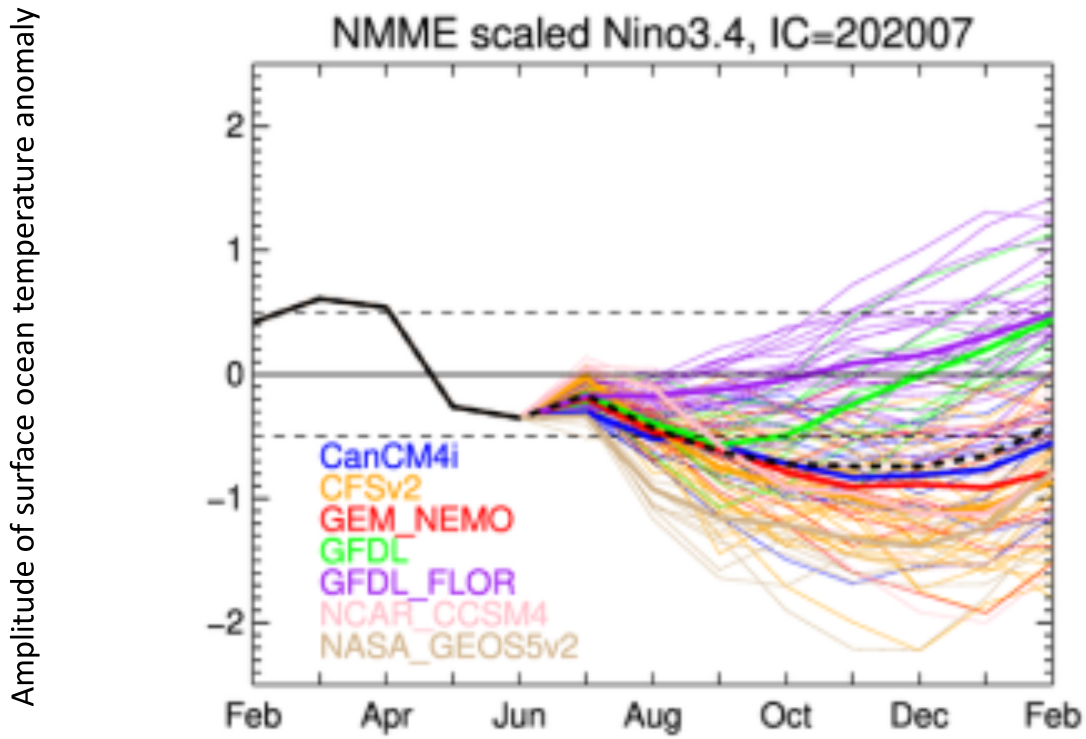
La Niña forecast plumes for the recent event (2020/21)

Shows forecast uncertainty due to:

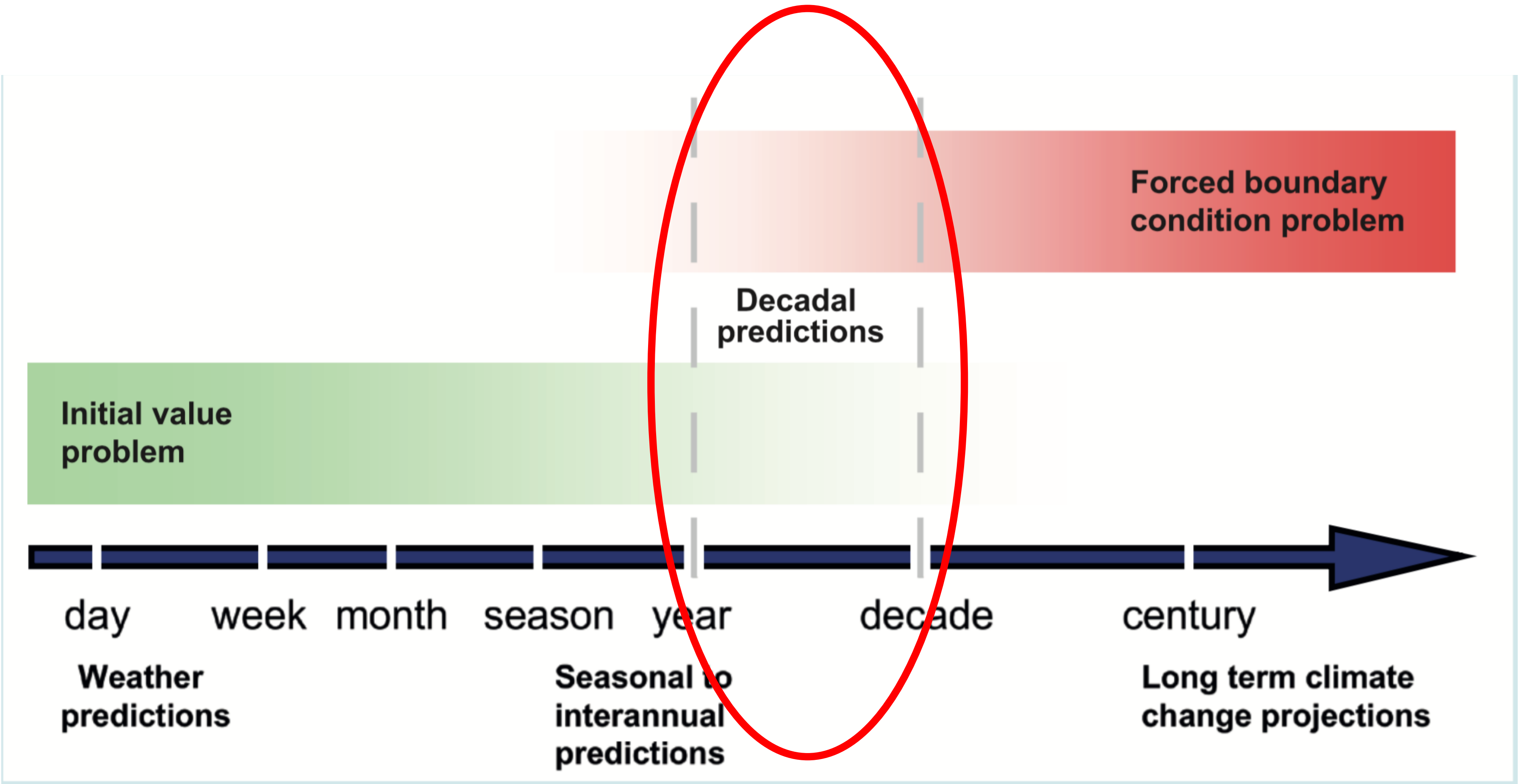
- Model
- Initial (atmospheric) conditions

In general, "best" forecast is the ensemble mean of all forecasts, but (if this model was perfect) all of these plumes are equally likely

La Niña forecasts (all models, ensemble members): starting July 2020



Predictions and projections



To make a decadal forecast, we need

- Large ensemble using different atmospheric initial conditions
- Good initialization of the ocean
- Model simulation that realistically captures climate variability ("internally generated variability")
- Forecasts of anthropogenic changes in atmospheric composition ("external forcing")
  - Can't forecast volcanic eruptions though
  - Solar? Not very well but a little

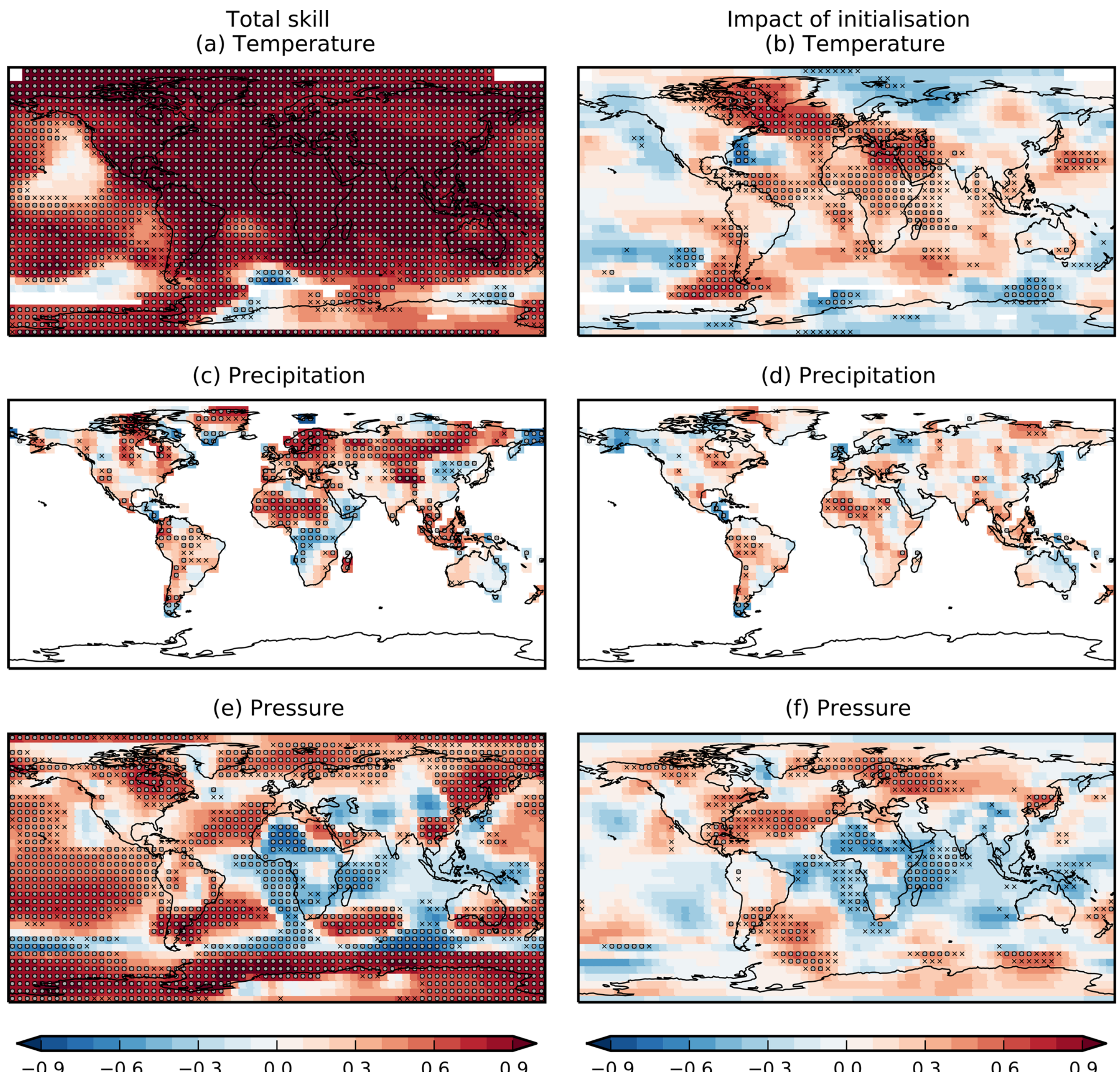
Skill of decadal prediction, for retrospective forecasts 1960-2005

Predictions are averaged over “Years 2-9”

Most skill due to trend

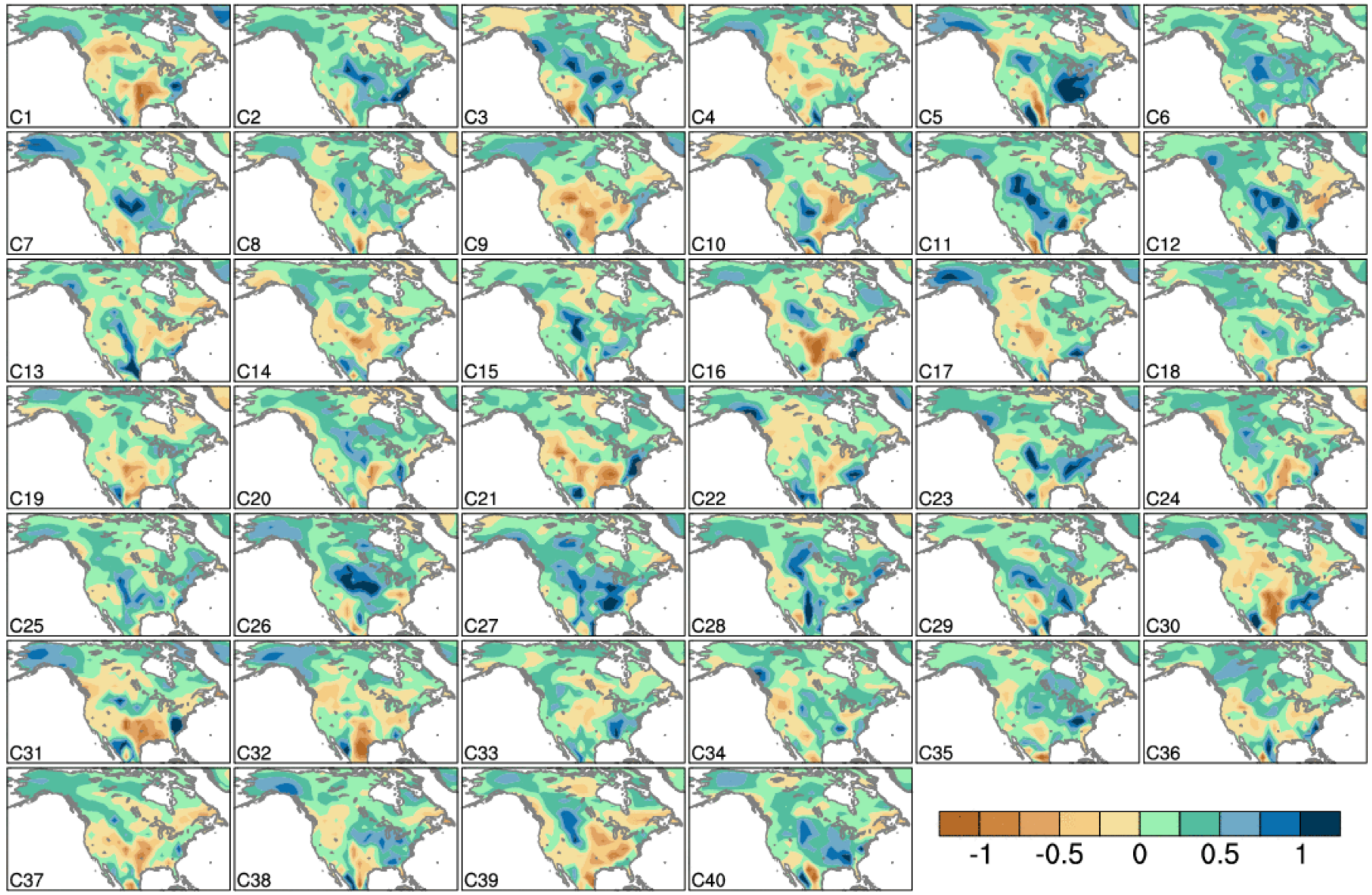
“Initialization” skill, reflecting natural (“internal”) variability, is mostly from first few years

Skill measure is ”anomaly correlation”, captures extent to which forecasts got the anomaly sign right



Different precipitation trends due to internal variability alone

Large climate ensemble: 40 climate "forecasts" using *same* anthropogenic forcing (2010-2060) and slightly different initial atmosphere conditions



Summer precipitation trends (2010-2060; mmd^{-1} per 51 years) from each CCSM3 ensemble member, forced with the same time-evolving external forcing of the A1B greenhouse-gas scenario. From Deser et al. (2013)

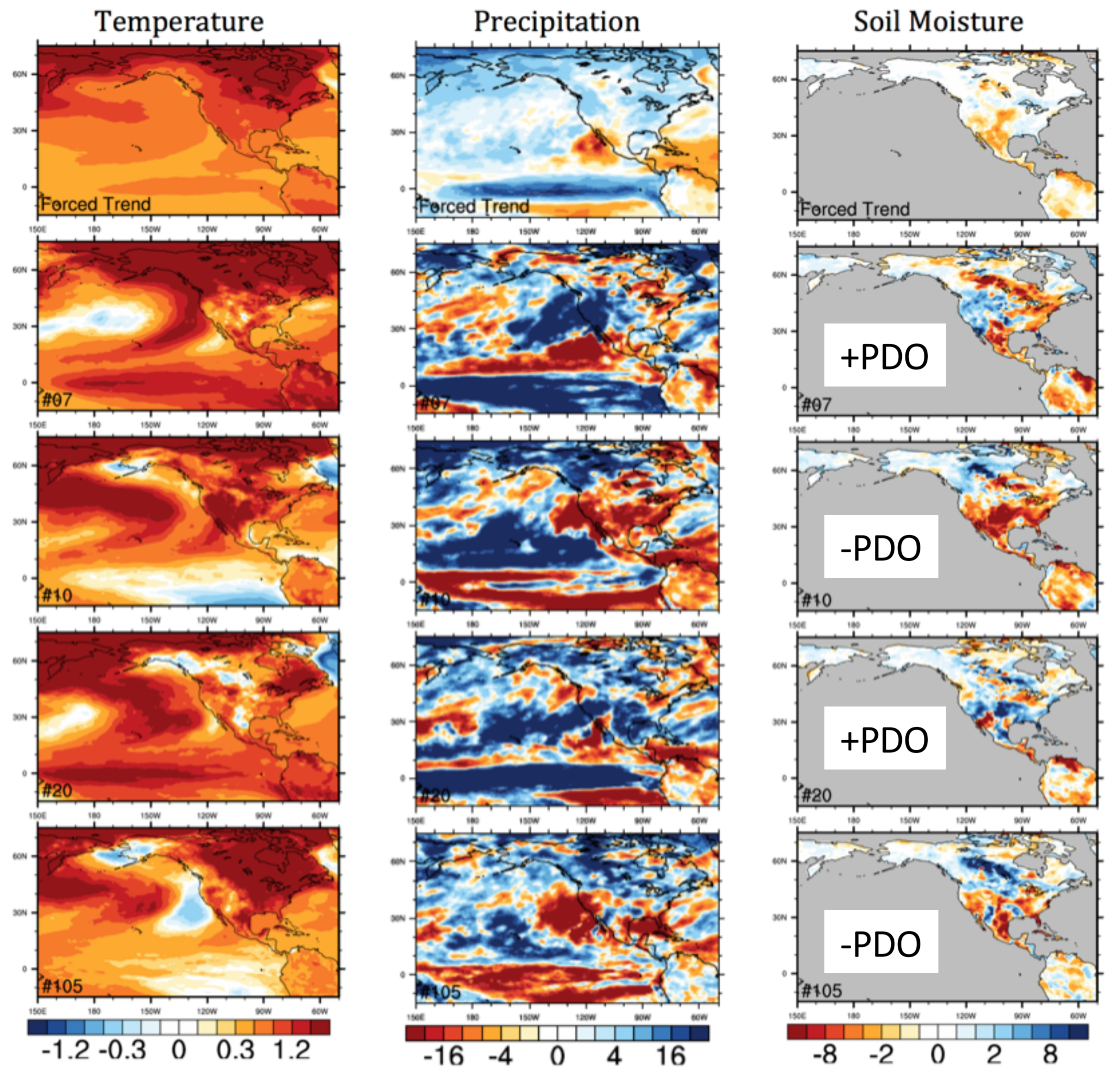
PDO/ENSO impacts on projected (NCAR model) hydroclimatic changes, 2016-2035

Top: Ensemble mean trend (externally forced change)

Rows 2-5: Selected ensemble members highlighting influence of PDO/ENSO like variability

positive PDO/ENSO: #7, #20
negative PDO/ENSO: #10, #105

Units: °C for temperature, % change for precipitation and soil moisture.

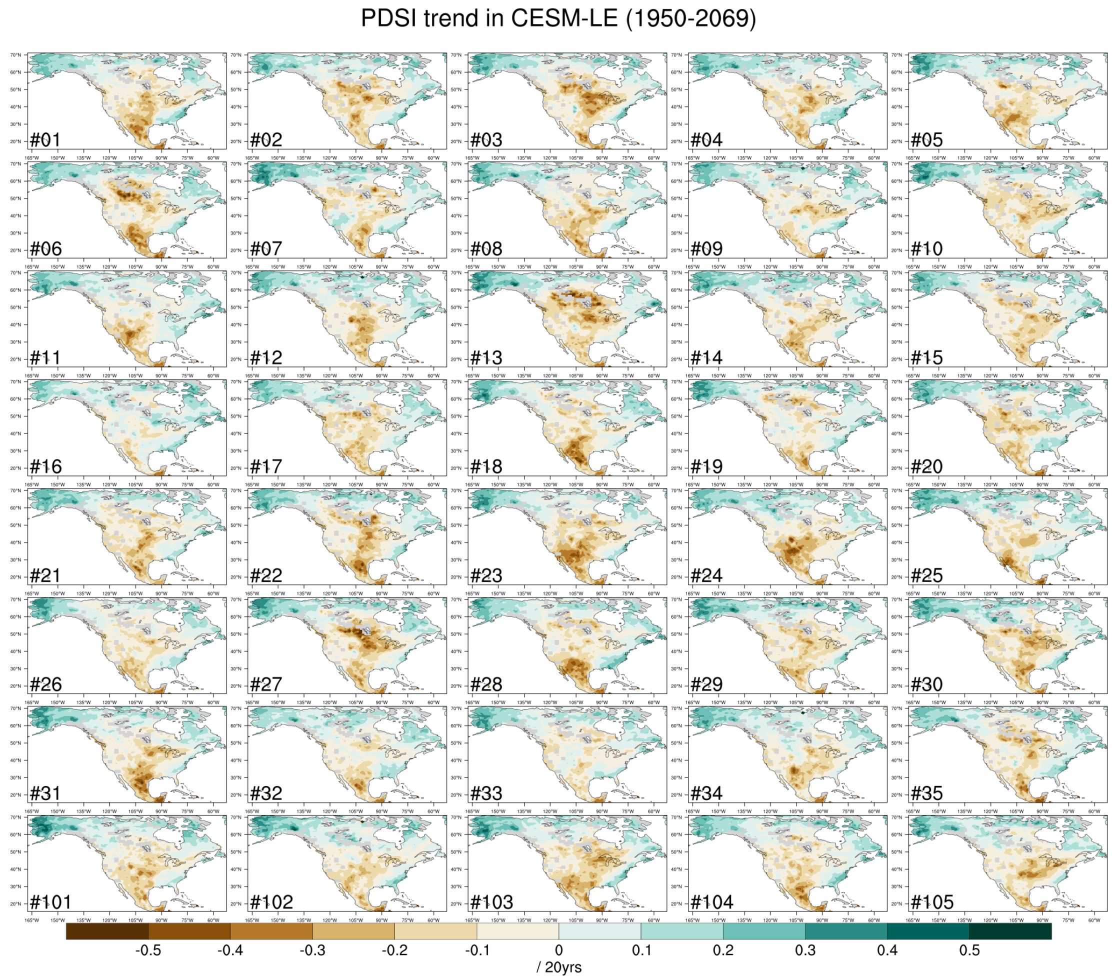


Uncertainty in drought trends is potentially quite large

Substantial uncertainty in long-term (120-yr!) drying trend between different ensemble members

Using Palmer Drought Severity Index (PDSI) as proxy for soil moisture (e.g., surface dryness /wetness); brown means drier

Another problem: coupled models have trouble getting Pacific SST anomaly evolution right (ENSO/PDO)



Sources of near-term forecast uncertainty

- “Internal” (natural weather/climate) variability
- Scenario (emissions, other “external forcing”) uncertainty
- Model error (model simulations of the above will differ)

Other sources of uncertainty (Hawkins and Sutton)

Suggests that relative importance of sources of uncertainty varies due to

1) forecast lead time
2) region (size)

[My opinion is that they underestimate impact of internal variability and model error, especially for precipitation]

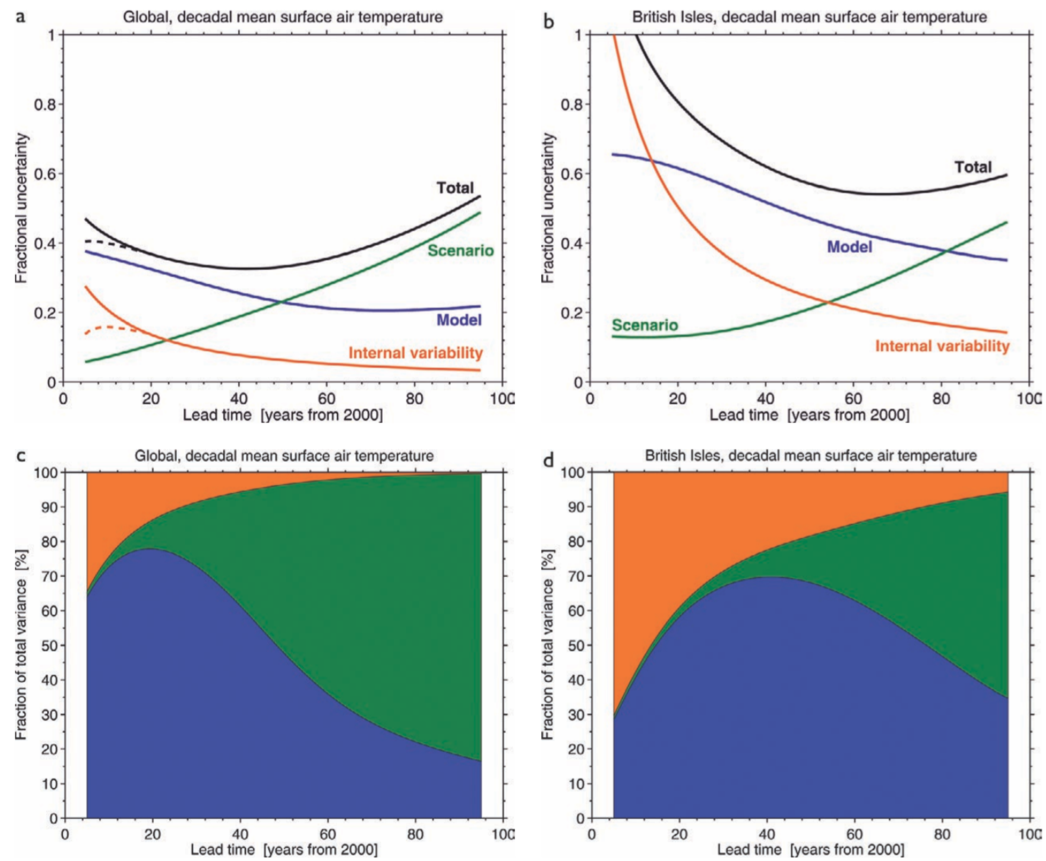


Fig. 4. The relative importance of each source of uncertainty in decadal mean surface temperature projections is shown by the fractional uncertainty (the 90% confidence level divided by the mean prediction) for (a) the global mean, relative to the warming from the 1971–2000 mean, and (b) the British Isles mean, relative to the warming from the 1971–2000 mean. The importance of model uncertainty is clearly visible for all policy-relevant timescales. Internal variability grows in importance for the smaller region. Scenario uncertainty only becomes important at multidecadal lead times. The dashed lines in (a) indicate reductions in internal variability, and hence total uncertainty, that may be possible through proper initialization of the predictions through assimilation of ocean observations (Smith et al. 2007). The fraction of total variance in decadal mean surface air temperature predictions explained by the three components of total uncertainty is shown for (c) a global mean and (d) a British Isles mean. Green regions represent scenario uncertainty, blue regions represent model uncertainty, and orange regions represent the internal variability component. As the size of the region is reduced, the relative importance of internal variability increases.

Regional sources of uncertainty (Hawkins and Sutton)

Similar to previous slide but gives more of a regional picture

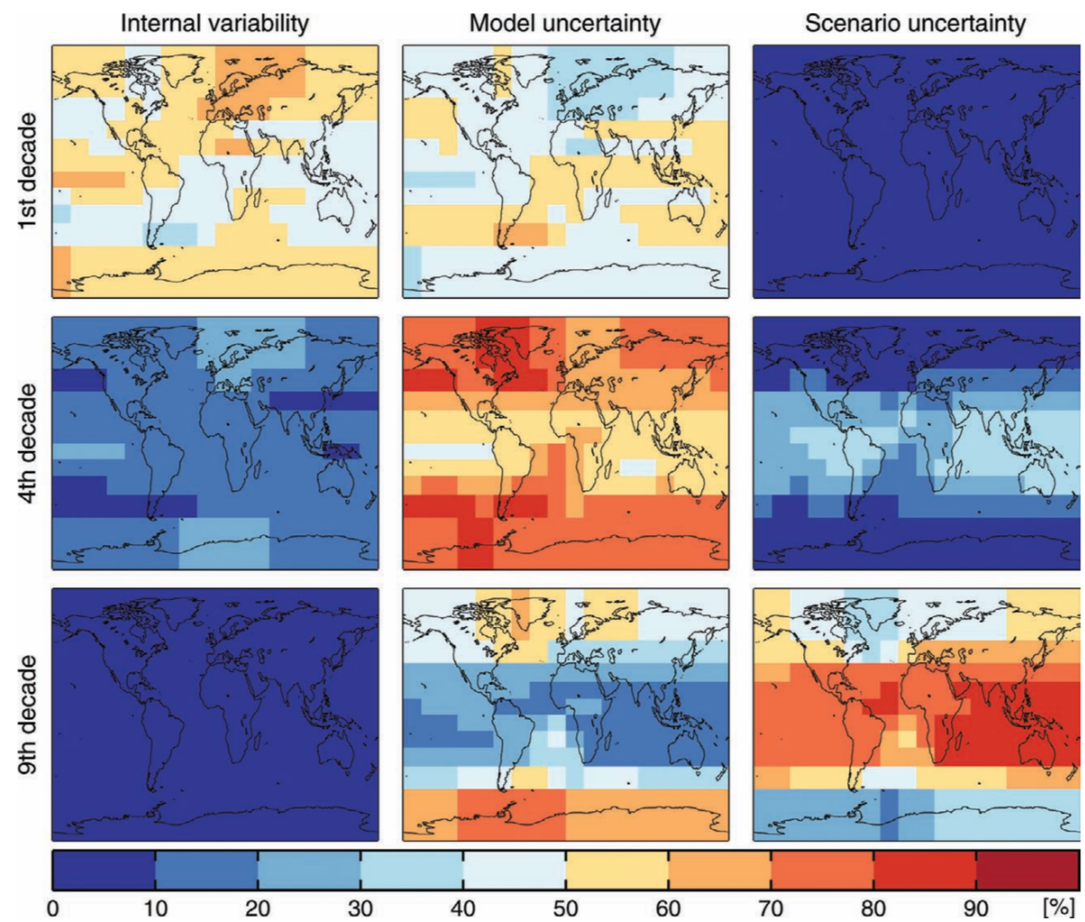


FIG. 6. Maps of the sources of uncertainty for decadal mean surface temperature for various lead times give information on where any reduction in uncertainty will have the most benefit. The columns show the total variance explained by (left) internal variability, (middle) model uncertainty, and (right) scenario uncertainty for predictions of the (top) first, (middle) fourth, and (bottom) ninth decade. It should be noted that (i) even on regional scales, the uncertainty due to internal variability is only a significant component for lead times up to a decade or two, (ii) the largest differences between models occur at high latitudes where climate feedbacks are particularly important, and (iii) even by the end of the century, the emissions scenario is less important than model uncertainty for the high latitudes but dominates in the tropics.

Discussion questions

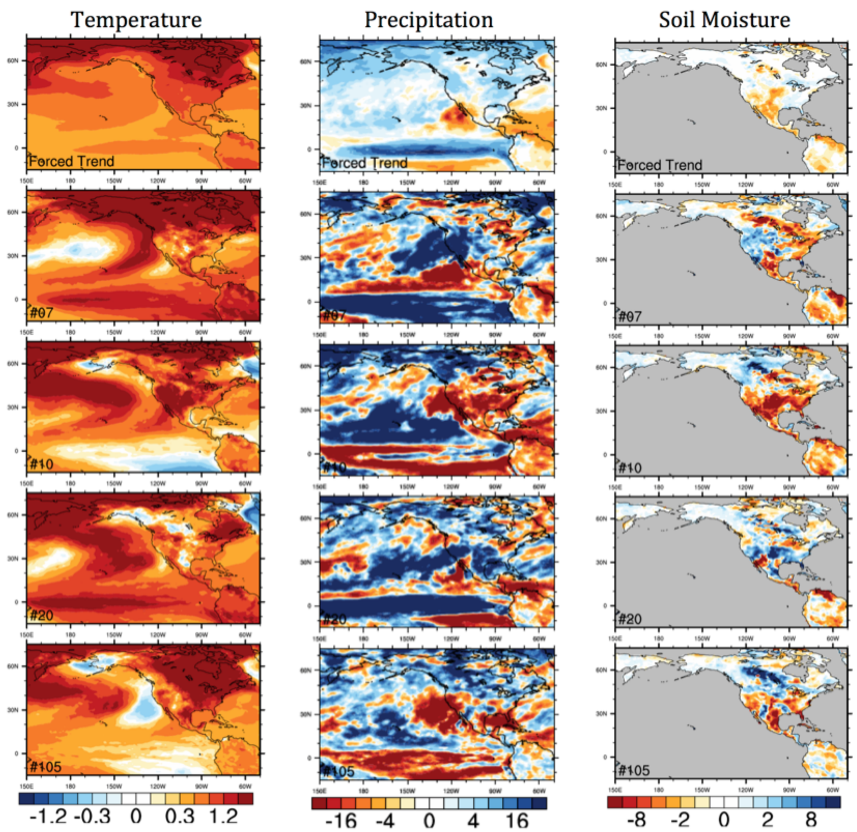
- How might adaptation policy based on near-term climate forecasts deal with uncertainty?
- Consider that the impact of forecast uncertainty could depend on:
  - forecast variables (e.g., max and min temperature, precipitation)
  - regions (e.g., southwest U.S. vs. Great Plains)
  - seasons
  - forecast lead times (e.g., 5, 10, 20 yrs, or longer)

Discussion questions

- How might this uncertainty affect the politics of formulating a response (either prevention or adaptation) to anthropogenic change? Should it? Why or why not?

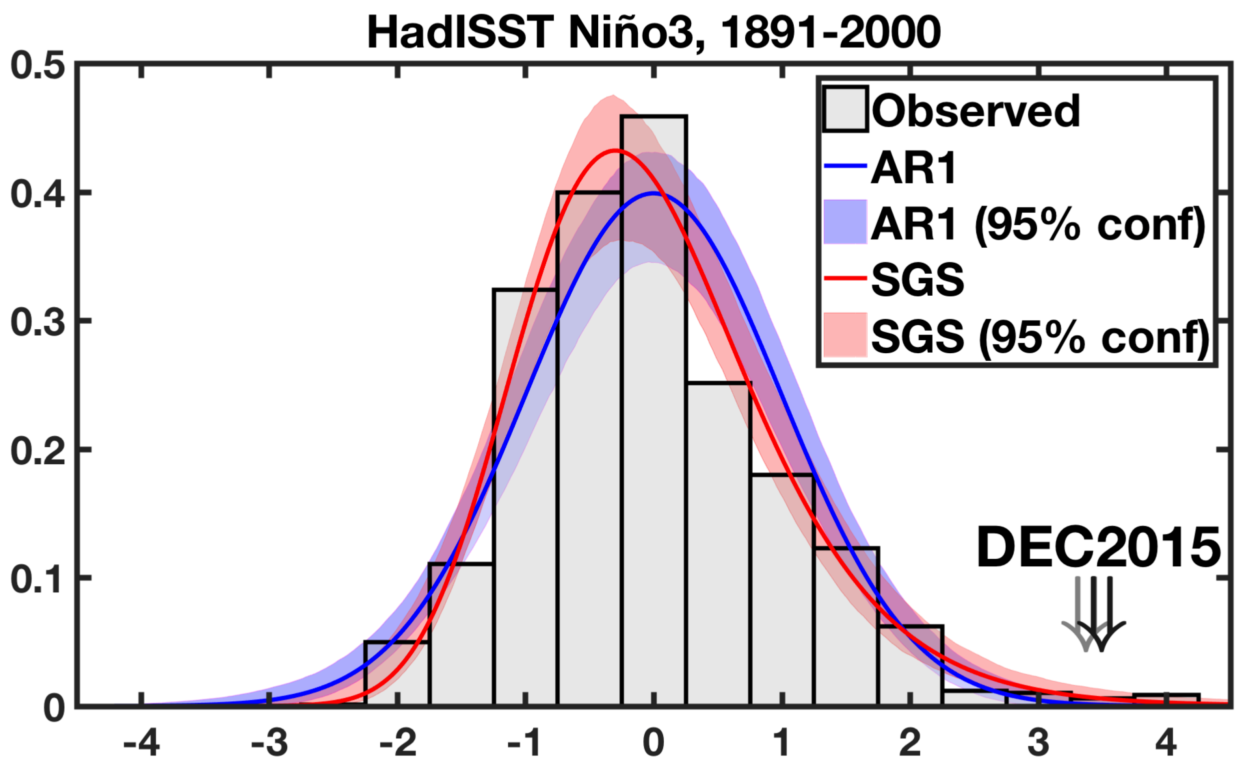
Homework question

- Produce a communication strategy for the pictured climate forecast ensemble covering the next 20 years for the U.S. [Recall that the top row is the ensemble mean.]
- Consider how different audiences (policymakers, general public, land/water managers) may respond, especially to a discussion of uncertainty.



Extra slides

Histogram of Niño3 (eastern equatorial Pacific) sea surface temperature anomalies



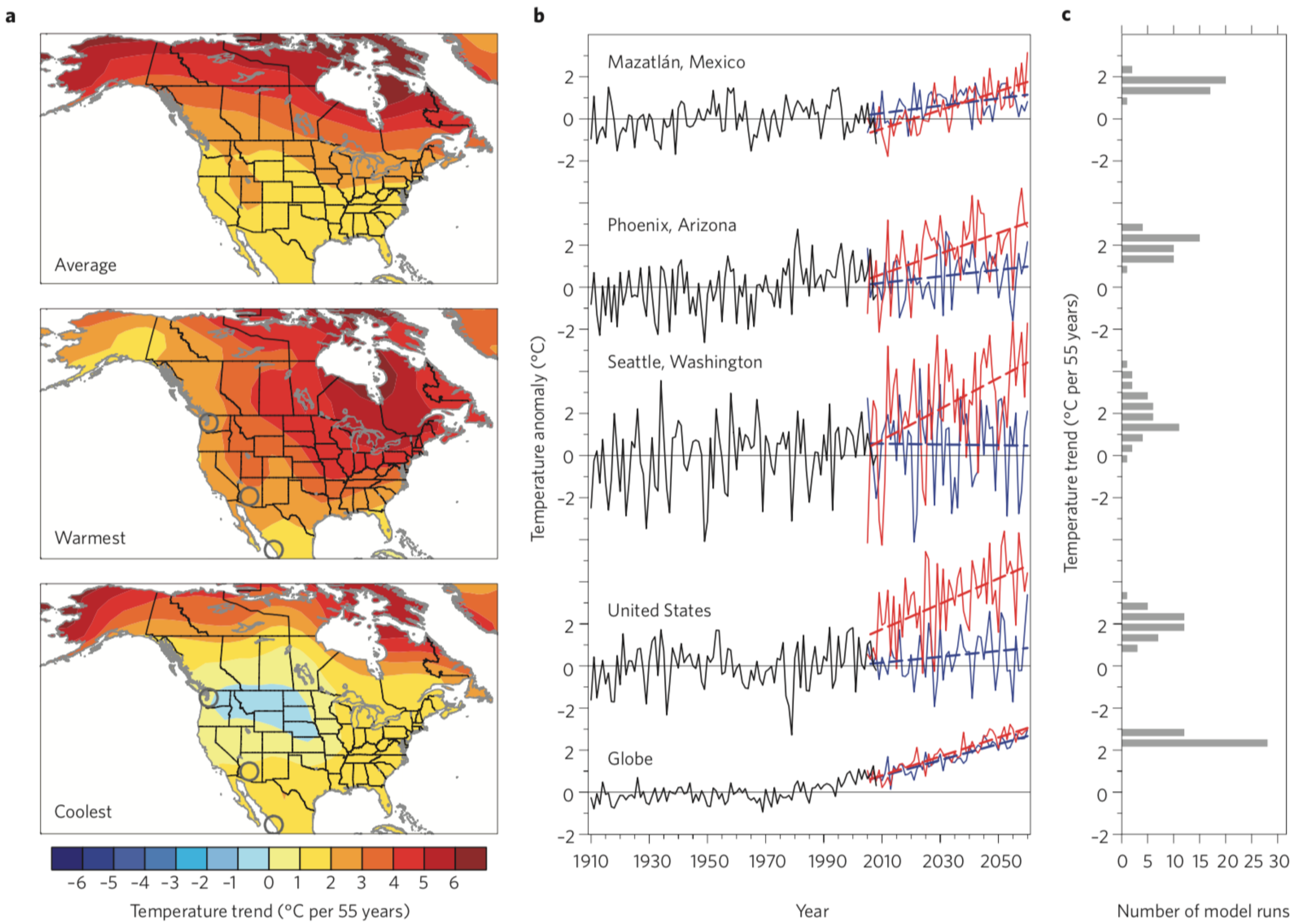


Figure 1 | Range of future climate outcomes. a, December–January–February (DJF) temperature trends during 2005–2060. Top panel shows the average of the 40 model runs (all values are statistically significantly different from zero at the 5% confidence level); middle and bottom panels show the model