Decadal Predictions: State of the Science

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Why the emphasis on decadal predictions?

- **Societal need** for near term/decadal predictions of climate for decision support (Vera et al. 2010)
  - Actual time evolving predictions rather than uninitialized projections[1].

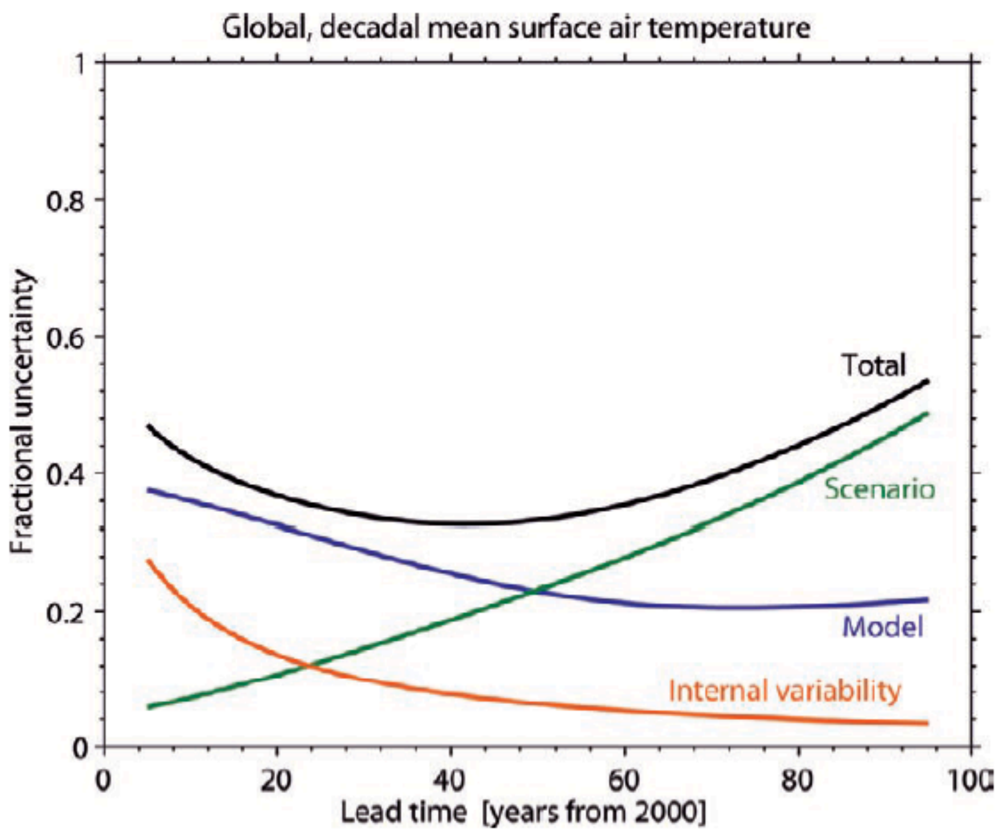
- Research shows **potential (and some evidence) for prediction skill** on decadal timescales

- **Less sensitive to emissions scenario**

[1] IPCC definition is predictions are initialized, projections are uninitialized

Kirtman et al. 2013, IPCC

Emissions scenario less important on decadal timescales



- CMIP5 decadal predictions used the **RCP4.5** scenario. (Meehl et al. 2014)

Hawkins and Sutton 2009

Bridge gap between ENSO forecasting and future climate change projections

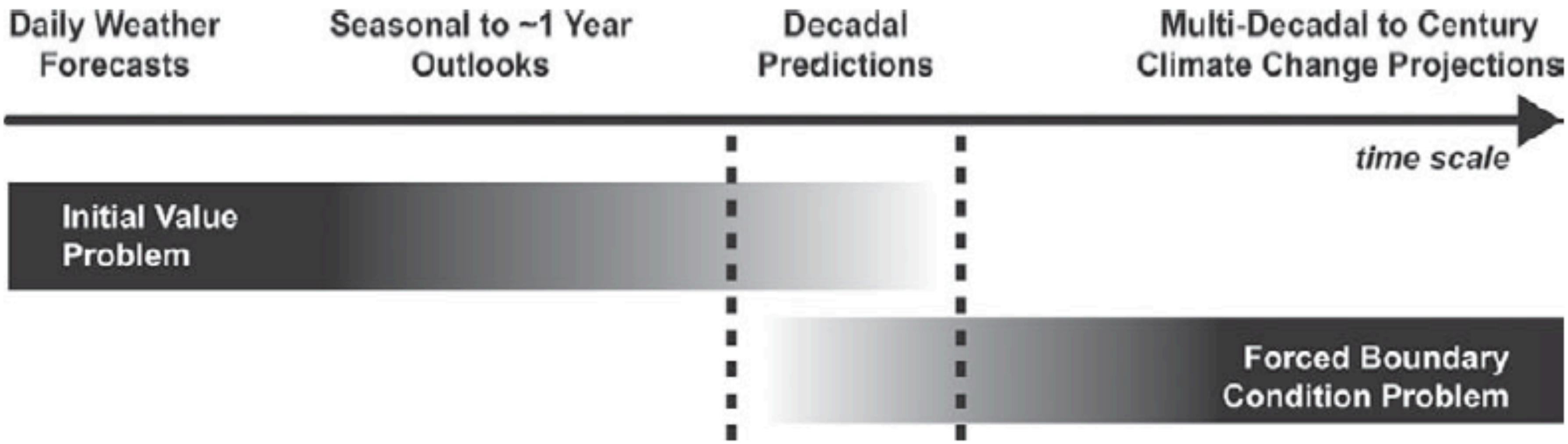
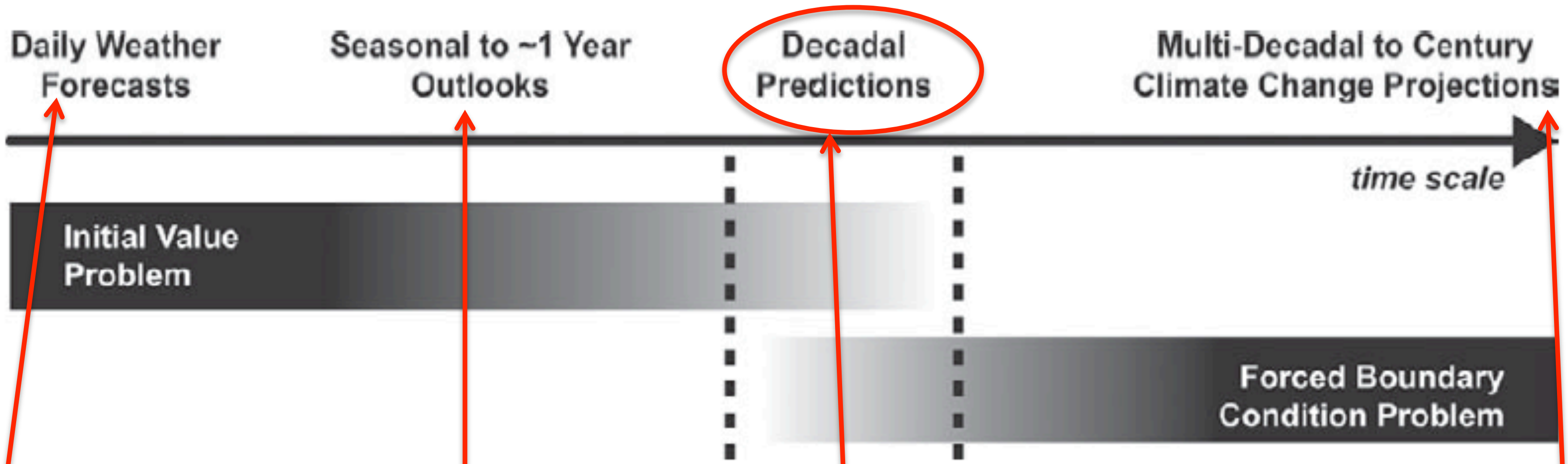


Figure 2 Meehl et al. 2009 BAMS

Bridge gap between ENSO forecasting and future climate change projections



Synoptic weather: 2 weeks (Lorenz 1963)

ENSO evolves more slowly: 6-12 months

What's the "sweet spot"? (out 10-30 years defined as "decadal")

Long-term trends based on GHG forcing

Figure 2 Meehl et al. 2009 BAMS

What are the CMIP5 decadal predictions?

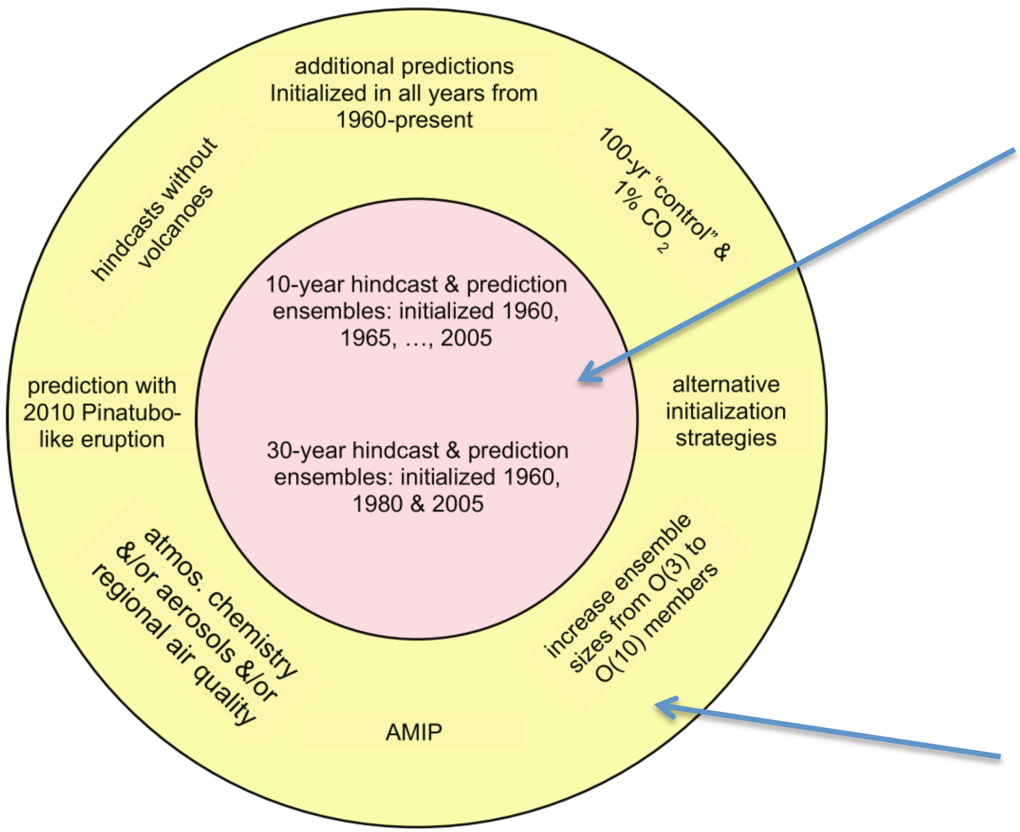


FIG. 3. Schematic summary of CMIP5 decadal prediction integrations.

- **Two core sets of near-term experiments**
  - 10-year hindcasts
  - 30-year hindcasts (out to 2035)
- Specialized simulation options

Taylor et al. 2012 BAMS

Aim is to understand predictibility, merits of data assimilation approaches, and limitations of current observations

Table 1. Continued.

Experiment description	CMIP5 label	AOGCM	ESM or EMIC	High resolution[a]	Major purposes
Mid-Holocene conditions (as called for by PMIP)	midHolocene	X	X		Evaluation
Last Glacial Maximum conditions (as called for by PMIP)	lgm	X	X		Evaluation
Natural forcing for 850–1850 (as called for by PMIP)	past1000	X	X		Evaluation, natural variability
Decadal hindcasts/predictions, some extended to 30 yr	decadalXXXX[d]	X			Predictability, prediction, evaluation
Hindcasts but without volcanoes	noVolcXXXX[d]	X			Predictability
Decadal forecast with Pinatubo-like eruption in year 2010	volcIn2010	X			Predictability, prediction
SST and some other conditions for 2026–35 specified from a coupled model experiment	sst2030			X	Projection

[d] The "XXXX" is a generic representation of the year in which the decadal prediction was initiated. As an example, a simulation focusing on the 10-yr period from Jan 1966 to Dec 1975 will typically be initiated sometime between 1 Sep 1965 and 1 Jan 1966 and would be labeled "decadal1965."

Taylor et al. 2012 BAMS

Decadal predictions and projections have built-in skill[1] from:

1 Climate change commitment

2 The forcing from increasing greenhouse gases

} Radiative/ external forcing

CMIP3 models can already simulate the magnitude of observed decadal surface temperature variability over land (IPCC 2007 WGI Fig 9.8)

[1]Barring volcanic eruption

Meehl et al. 2009; Lee et al 2006

Skill from **initialization** versus radiative forcing depends on time horizon, variable, & region

- **Initialization** contributes most skill in
  - **first few years:** annual mean temperature
  - **a few years to a decade:** global mean surface temperature and temperature over the North Atlantic, regions of the South Pacific and the tropical Indian Ocean

- **Radiative forcing** contributes most skill
  - **Beyond first few years:** for annual and multi-annual averages of temperature and precipitation

Kirtman et al. 2013, IPCC

Some general findings

- For initialized decadal hindcasts, **multimodel ensemble outperforms most single model results** (Chikamoto et al. 2012a, Kim et al. 2012, and Smith et al. 2012b.) (From Meehl et al. 2014 BAMS)

- Potential predictibility:
  - Greater for ocean heat content than atmospheric or land variables (Hermanson and Sutton 2010) (From Kirtman et al. 2013 IPCC)
  - Ocean skill increases with latitude and depth (Power and Colman 2006) (From Kirtman et al. 2013 IPCC)
  - Greater at higher latitudes (extratropical oceans) than over land (Figure 11.1, Kirtman et al 2013, IPCC)
  - Lower for tropics and over land, where skill mostly from external forcing (Figure 11.1, Kirtman et al. 2013, IPCC)

Decadal phenomena that could contribute to skill

- **Pacific**
  - 11-year solar cycle with tropical Pacific SSTs
  - Pacific Decadal Oscillation (PDO), North Pacific Index (NPI), Interdecadal Pacific Oscillation (IPO)
- **Atlantic**
  - Atlantic meridional overturning circulations (AMOCs)
    - Strong ties with North Atlantic Oscillation
  - Atlantic Multidecadal Oscillation (AMO), Atlantic multidecadal variability (AMV)

Meehl et al. 2009

Technical challenges remain

- **Model initialization/data assimilation**
  - Many different methods by different modeling groups (Table 1, Meehl et al. 20014 BAMS)
  - For drift: Full-field initialization vs anomaly initialization (Meehl et al. 2014 BAMS)

- **Limited availability of observations** (Goddard et al. 2012 BAMS)

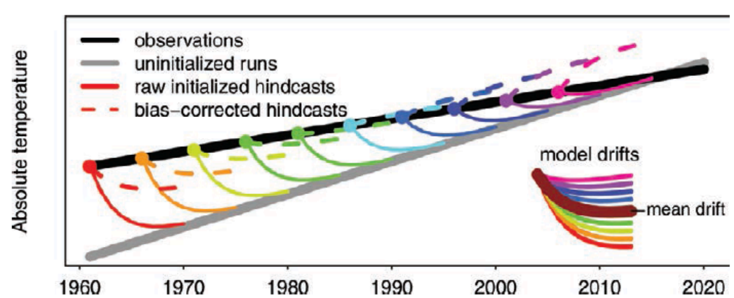
- **Dynamical model limitations** (Goddard et al. 2012 BAMS)

Kirtman et al. 2013, IPCC

Technical challenges remain

- **Predictions require bias adjustment[1]**
  - Models drift from the observed initial state to its own preferred state, sometimes rapidly.
  - Mean bias adjustment does not address issues such as potential trends (time dependence) in the drift/ bias.
    - i.e., correction is **more complicated** than for centennial runs.

Fig. 1. Meehl et al. 2014 BAMS



[1] CMIP–WGCM–WGSIP Decadal Climate Prediction Panel, 2011: Data and bias correction for decadal climate predictions. WCRP Rep., ICPO Publ. Series 150, 3 pp.

[Available online at www.wcrp-climate.org /decadal/references/DCPP_Bias_Correction.pdf.]

Recommendation for bias correction:

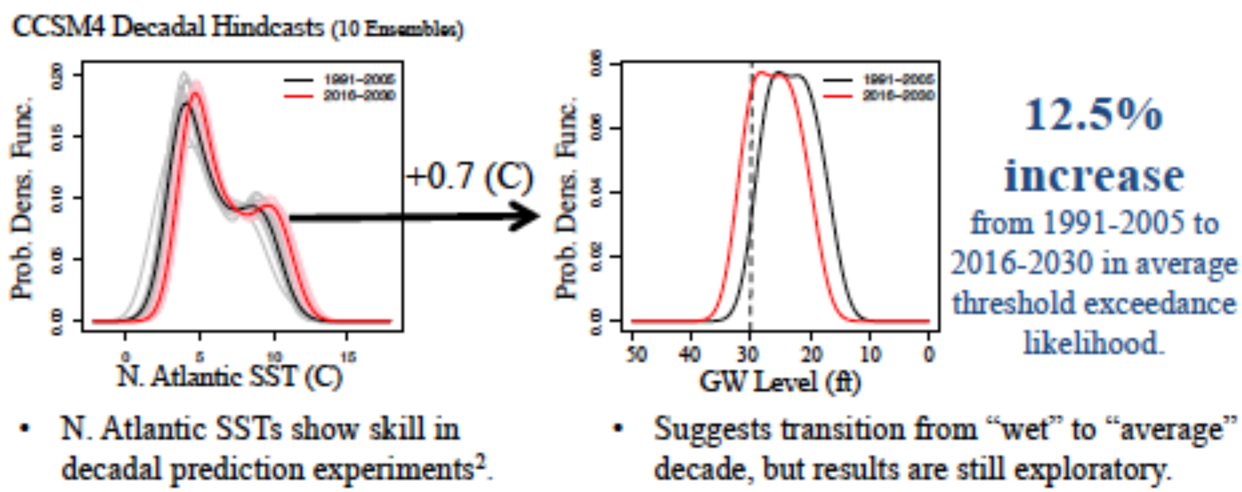
- "Most users will find it difficult to bias correct the decadal prediction runs; it is therefore recommended that analysis of the near-term simulations be limited to the four variables that the modeling groups themselves plan to bias correct: **near-surface air temperature, surface temperature, precipitation rate, and sea level pressure**."*

*I'm not sure if CMIP5 archive includes bias-corrected fields – need to check.

Taylor et al. 2012 BAMS

Bias correction option for 30-year hindcast:

- One method is to use the year 10 bias adjustment for years 11–30, assuming most of the drift occurs by year 10 (Meehl and Teng 2012, 2014).



(Towler et al., 2012 AGU poster)

Prediction quality needs to be assessed using a common verification framework

http://clivar-dpwg.iri.columbia.edu/

Decadal Predictability Working Group

IRI — U.S. CLIVAR Climate Variability & Predictability

Overview | Deterministic Metrics | Probabilistic Metrics

Hindcasts Skill Assessment

This website is a tool for the discusion within U.S. CLIVAR Working Group on Decadal Predictability of verification metrics towards the development of a verification framework for decadal hindcasts. If you have any questions or comments, please contact Lisa Goddard.

The different sections present results from the verification assessment of a few of the decadal hindcast experiments, mainly of CMIP5. For further details of the models and the forecast approach taken by each of the centers, please visit the CMIP5 data page: http://cmip-pcmdi.llnl.gov/cmip5/.

The verification metrics are chosen to answer specific questions regarding the quality of the forecast information. For example, they can identify where errors or biases exist in the forecasts to guide more effective use of them. The proposed questions address the accuracy in the forecast information and the representativeness of the forecast ensembles to indicate forecast uncertainty. Specifically, these questions are:

1. Do the initial conditions in the hindcasts lead to more accurate predictions of the climate?
2. Is the model's ensemble spread an appropriate representation of forecast uncertainty on average?

Need to use common obs →

Observational Datasets – Data Library

1. HadCRUT3v temperature anomalies (departures from 1958–2001 climatology)
2. GCOS GPCC precipitation anomalies (departures from 1958–2001 climatology)
3. NOAA NCDC ERSST v3b SST anomalies (departures from 1958–2001 climatology)

Indexes – Data Library

Sample MATLAB® Code for Data Library

HadCRUT3v temperature anomalies (departures from 1958–2001 climatology)

Data Library Ingrid Code:

```
expert
SOURCES .UEA .CRU .Jones .HadCRUT3v .varadjtanom
T (1961) (2008) RANGEEDGES
SOURCES .UEA .CRU .Jones .HadCRUT3v .varadjtanom
T (Jan 1958) (Dec 2001) RANGEEDGES
yearly-climatology sub
T yearlyAverage
```

Link to Data Library (**NOTE**: Use the " Data Files " link to save data in the preferred format)

Goddard et al. 2012 Clim Dyn

Temp: Widespread predictive skill of predictions vs. observations.

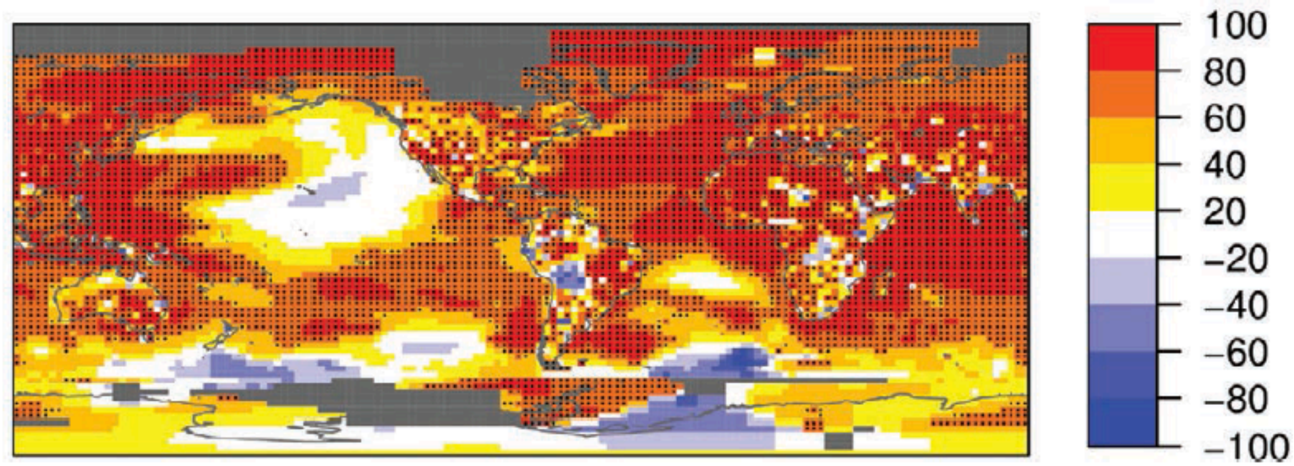


FIG. 4. Surface air temperature predictive skill (correlation with observations), predictions for years 6–9 averages based on CMIP5 multimodel ensemble mean hindcasts (see Table 1 for details). Results are from initialized hindcasts with 5-yr intervals between start dates from 1960 to 2005. Correlations are calcu-

Meehl et al. 2014 BAMS

Temp: Less skill added from initialization, varies spatially

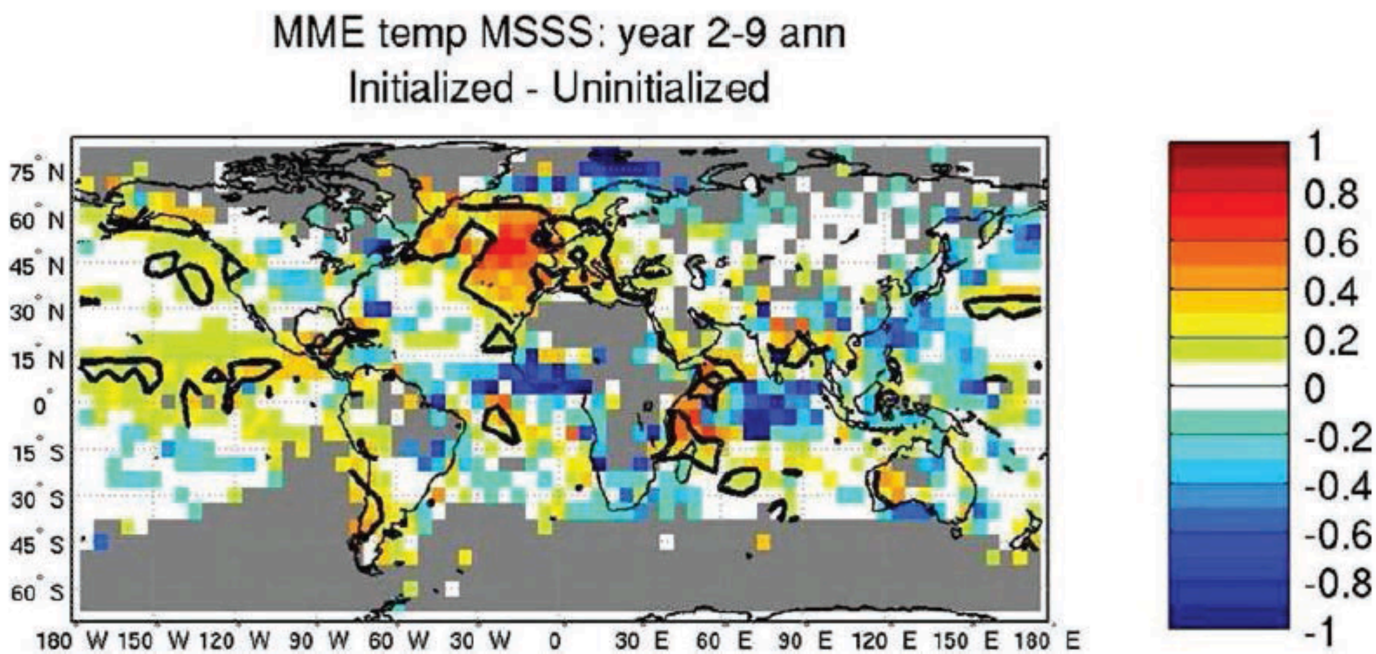


Fig. 3. Mean squared skill score (MSSS) differences for decadal temperature hindcasts from a 12-member multimodel ensemble from CMIP5, for the initialized hindcasts ("forecasts") minus the uninitialized hindcasts ("reference") as predictions of the observed climate. The forecast target is years 2–9 following

Meehl et al. 2014 BAMS

Oceans show highest skill, but skill source and regions vary

- **Indian Ocean**
  - Shows highest surface temp skill – due to external forcing from GHGs (so projections are also skillful)

- **Atlantic Ocean**
  - Many studies find that initialization improves the predictive skill of temperature in the North Atlantic – partially due to skillful AMOC prediction.
  - Some encouraging results for tropical Atlantic

- **Pacific Ocean**
  - Less skill than Indian and Atlantic Ocean
    - Interannual variability from ENSO, but debate on relationship between ENSO and decadal oscillations like PDO.
  - Some studies do show some improved skill from initialization, esp. in Western & South Pacific

Meehl et al. 2014 BAMS

Precipitation is less skillful than temp

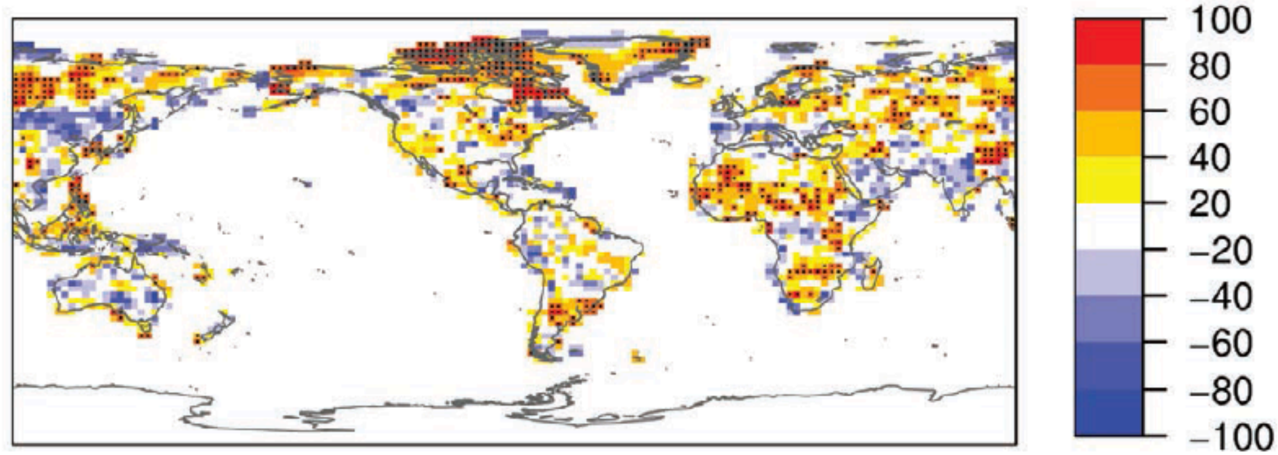


Fig. 8. Precipitation predictive skill (correlation with observations), predictions for years 6–9 averages based on CMIP5 multimodel ensemble mean hindcasts (see Table 1 for details). Results are from initialized hindcasts with 5-yr intervals between start dates from 1960 to 2005. Correlations are

Meehl et al. 2014 BAMS

Precipitation skill can be attributed mostly to radiative forcing (high confidence), initialization improves the skill very little (Goddard et al., 2013)."

Some skill in predicting **extreme** temperatures and precipitation

- 10% likelihood of occurrence (moderate extremes)
- Met Office Decadal Prediction System (DePreSys)
- Skill in extremes is similar but slightly lower than for mean
  - Some exceptions where there are trends in extremes (e.g., USA cold nights).
- Over multiyears, skill is from external forcing

Eade et al. 2012

- Skill in summer extreme indices, mostly from external forcing; DePreSys (Hanlon et al. 2013)

Decadal ocean skill could lead to skillful predictions over land

- Skillful North Atlantic Ocean SSTs could improve (i) rainfall over African Sahel, India, and Brazil, (ii) Atlantic hurricanes, and (iii) summer climate over Europe and America.
- Skillful Pacific SSTs could improve rainfall over North and South America, Asia, Africa, and Australia.
- Skillful Pacific *and* Atlantic SSTs could improve drought prediction over US.

Meehl et al. 2014 BAMS

Initialized predictions show less warming than projections.

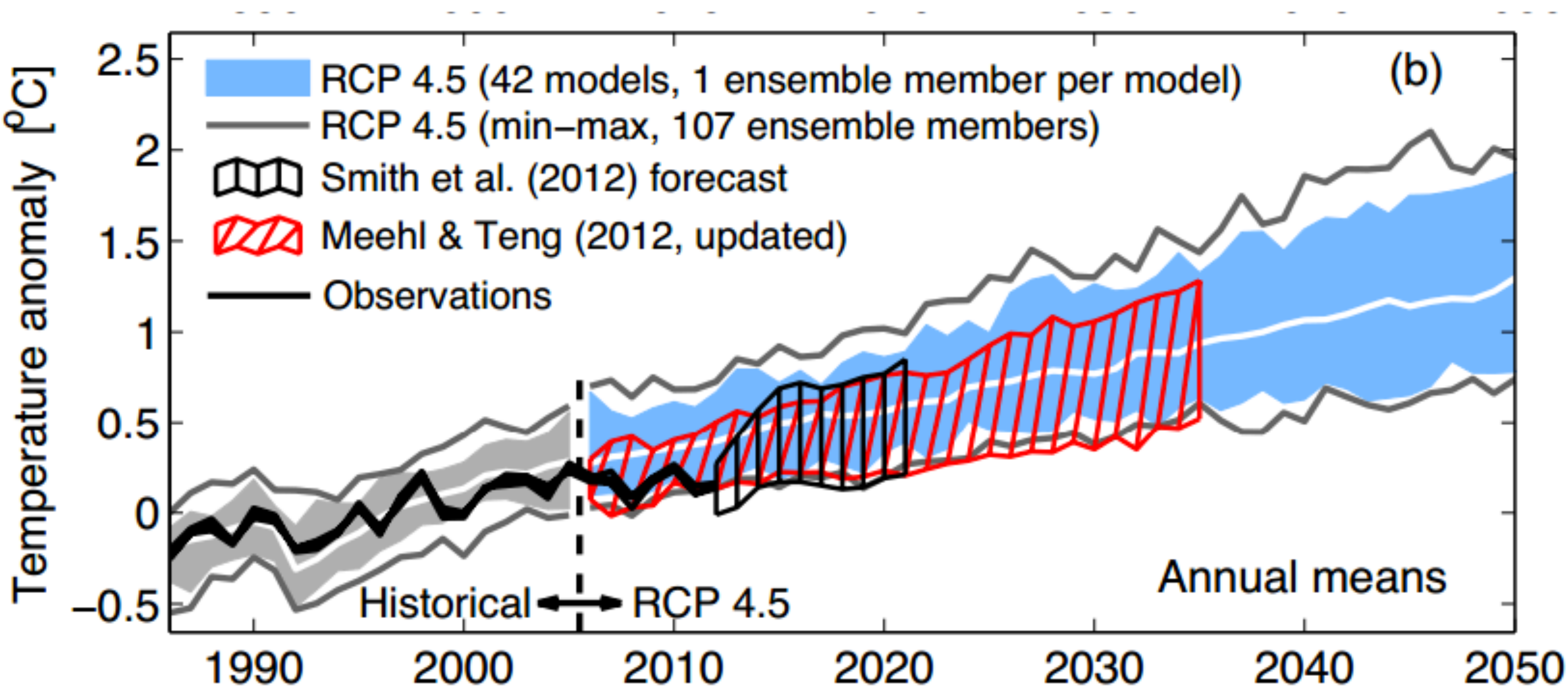


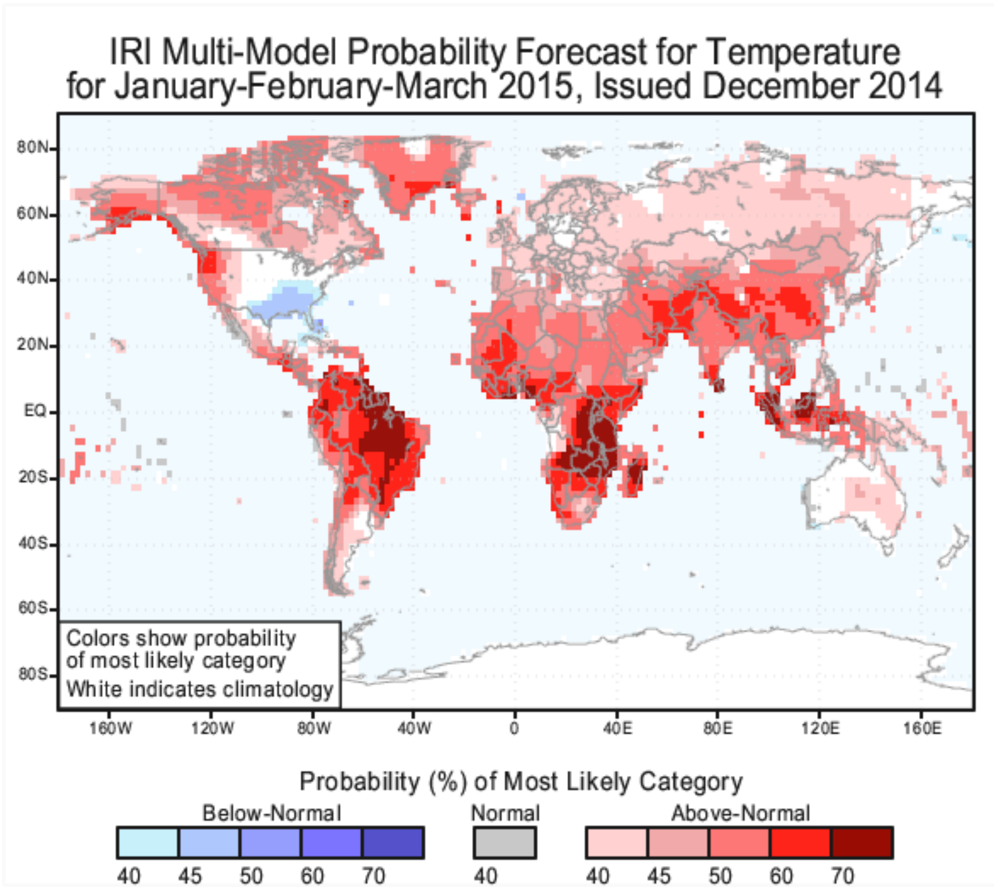
Figure 11.9b

Kirtman et al. 2013, IPCC

Decadal predictions are not considered "operational"

- "decadal predictions… are in an exploratory stage" (Taylor et al. 2012 BAMS)
- "… very much an experimental and nascent activity." (Goddard et al. 2010 Clim Dyn)
- "Due to the limitations, the estimates obtained from the hindcasts may provide a poor, and even misleading, guide to the future performance of the decadal prediction systems." (Goddard et al. 2010 Clim Dyn)

Decadal predictions have many features in common with seasonal forecasts



Goddard et al. 2012 BAMS;
Goddard et al. 2012 Clim Dyn.

Seasonal forecasts can provide a testbed for decadal predictions.

- **Build trust:** Seasonal forecasts offer opportunity to demonstrate performance over the recent past and over the next few seasons/years.
- **Increase uptake**: Using seasonal climate information will indirectly strengthen capacity for using climate info on longer time scales.

Goddard et al. 2012 BAMS

Additional/Upcoming decadal prediction experiments

- Seasonal-to-Decadal Climate Prediction for the Improvement of European Climate Services (SPECS)
- “Mittelfristige Klimaprognose” Germany (meaning decadal climate prediction) (MiKlip)
- New set of decadal climate predictions experiments into CMIP6.

Meehl et al. 2014 BAMS

The way forward

- **Increase understanding of climate and social influences on impacts**
- Leverage predictions in places where initialization improves skill (e.g., North Atlantic)
- Leverage projections in places where skill is due to external forcing (e.g., Indian Ocean) (**This is mostly what IPCC 2013 does; also can compare predictions and projections-extremes?).*
- Leverage NCAR medium/large ensemble where internal variability is important (e.g., local impacts)
- Develop generalized framework that will be ready when decadal predictions improve
  - Use seasonal forecasting as a "testbed"
  - Investigate how to "best" incorporate decadal predictions in decisions
  - Investigate "best" communication of decadal predictions

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