NOAA Earth System
Research Laboratory

Improving probabilistic forecast skill of temperature and precipitation using reforecasts. New results from ECMWF data sets.

Tom Hamill and Jeff Whitaker

NOAA Earth System Research Lab, Boulder, CO

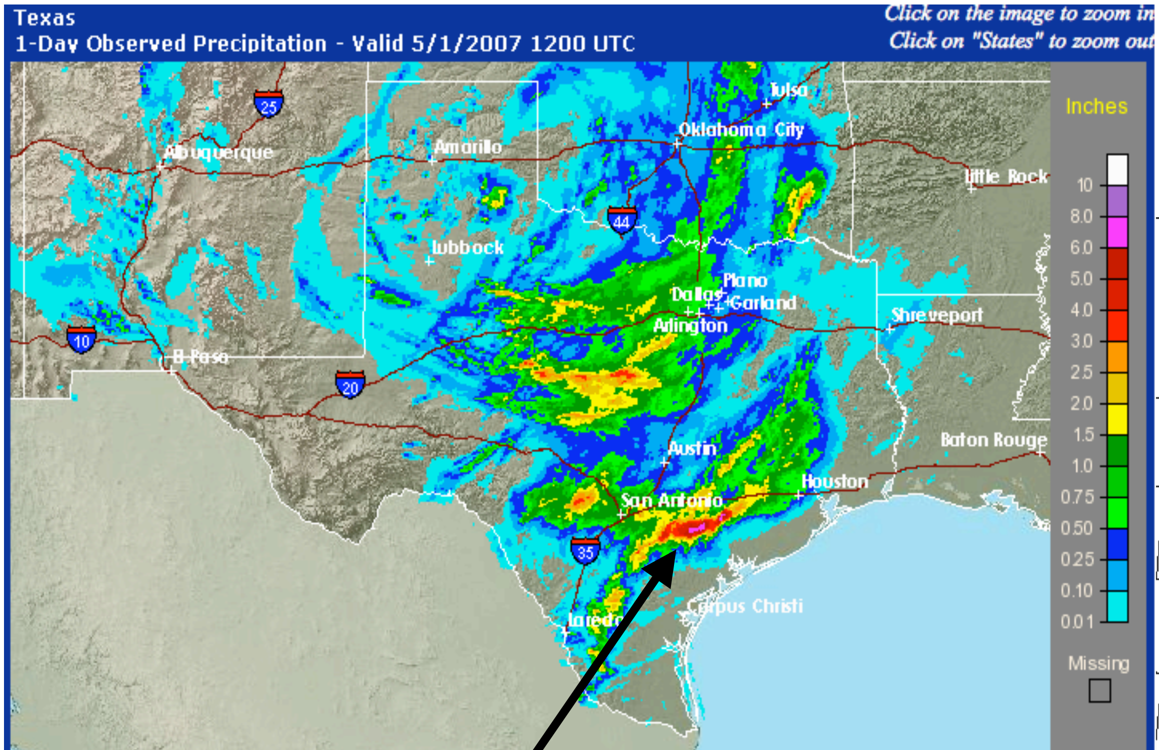
tom.hamill@noaa.gov ; esrl.noaa.gov/psd/people/tom.hamill

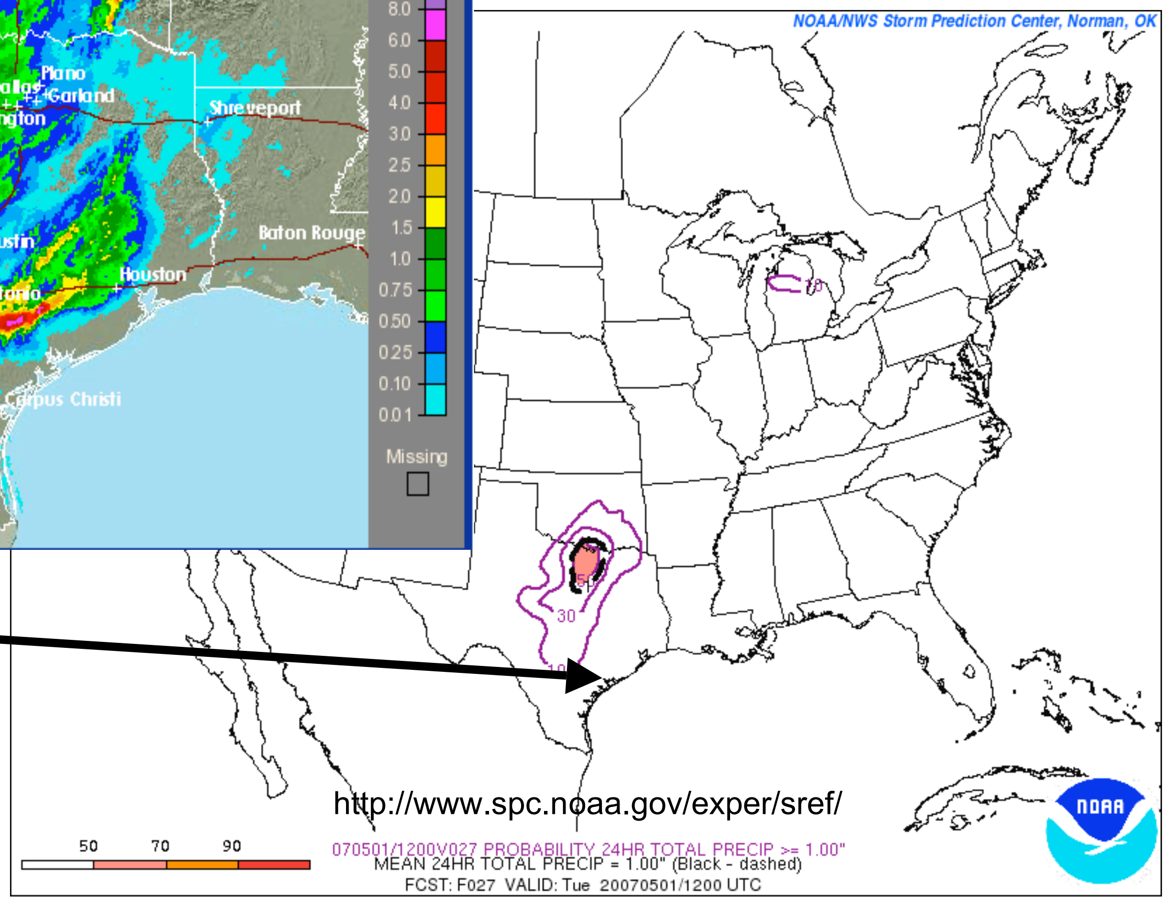
Renate Hagedorn

ECMWF, Reading, England

Problem with current ensemble forecast systems

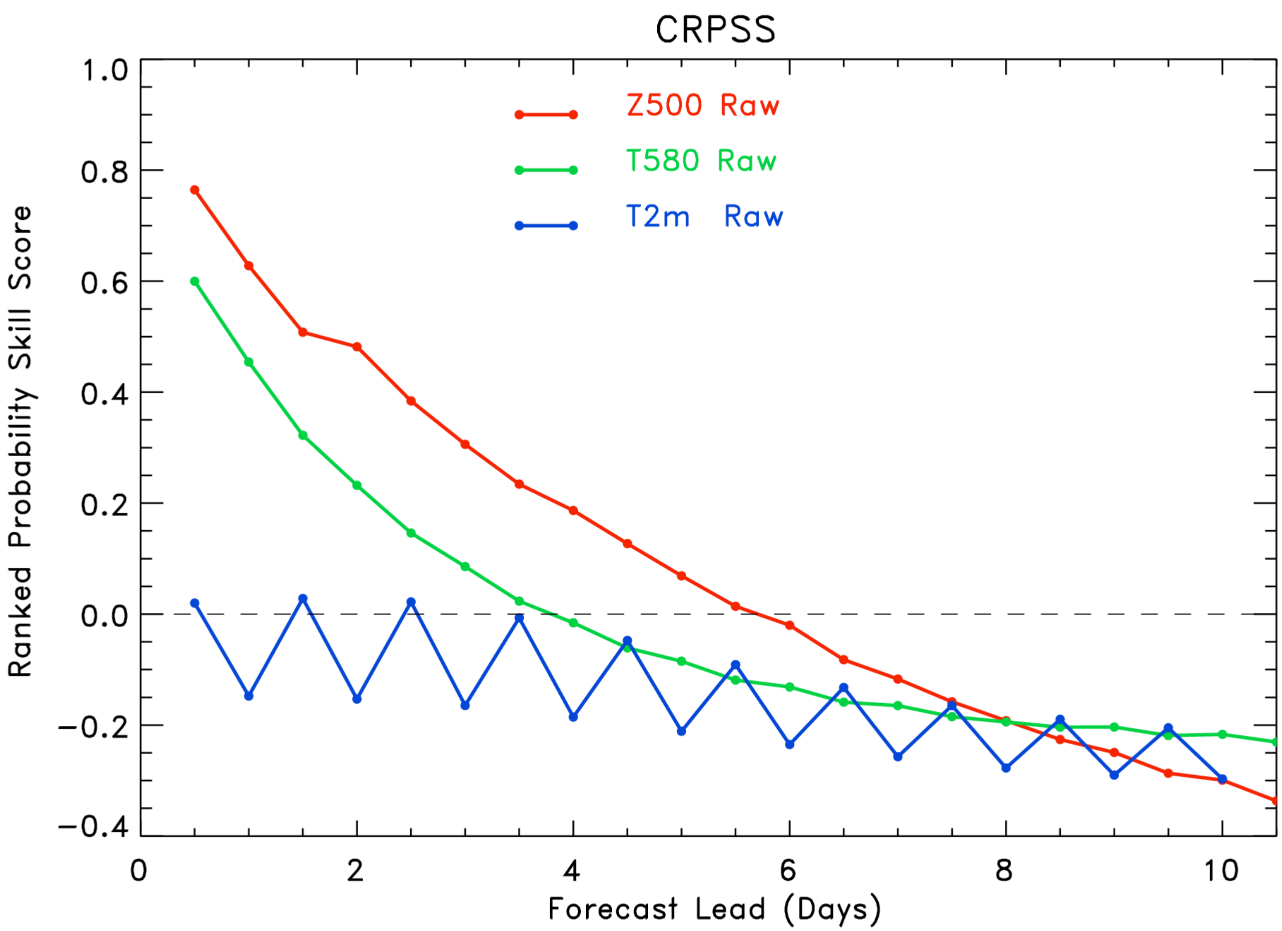
Forecasts may be biased and/or deficient in spread,
so that probabilities are mis-estimated. “Calibration” (statistical correction) needed.





Heavy rain in an area where none of the ensemble members predicted it.

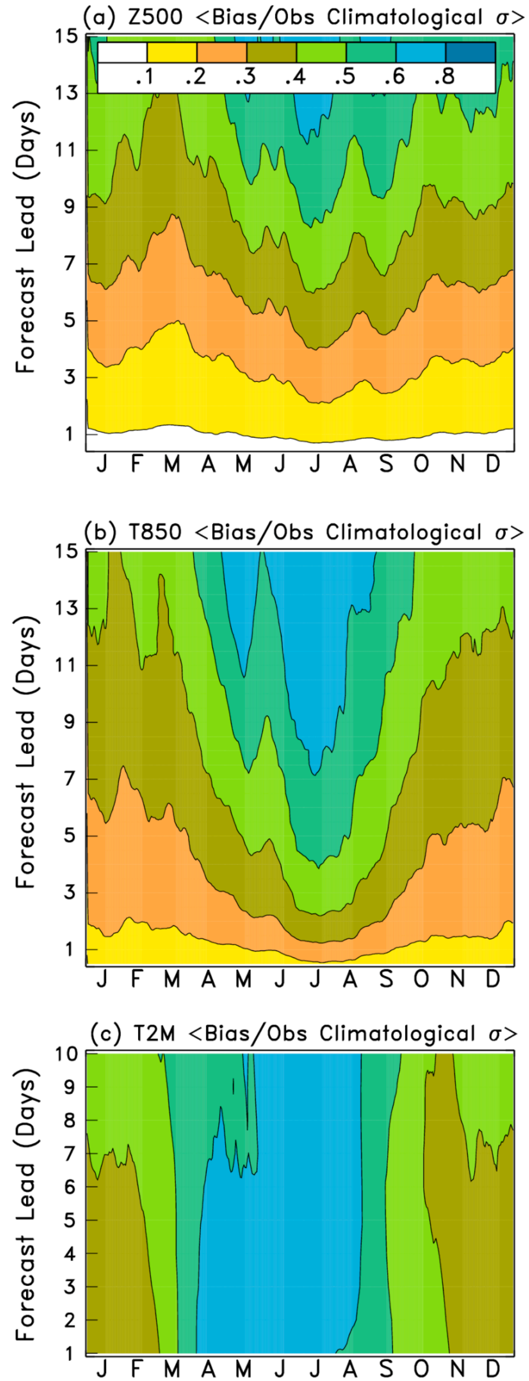
Skill of 500-hPa Z, 850-hPa T, and 2-m T from raw GFS reforecast ensemble

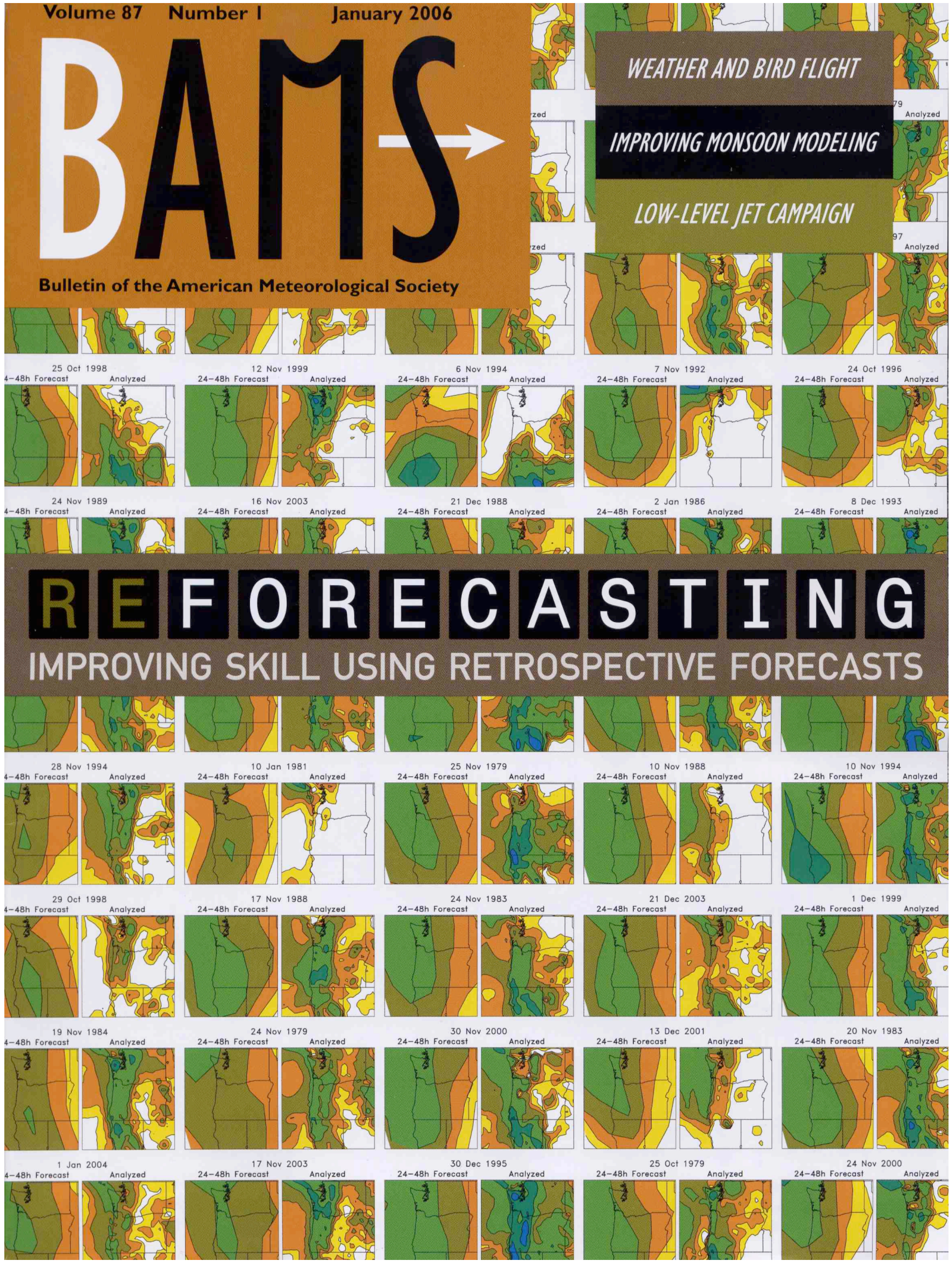


The one we probably care about the most, T_{2m}, scores the worst.

(1979-2004 data)

Forecast bias contaminates T_{2m} much more than Z_{500}

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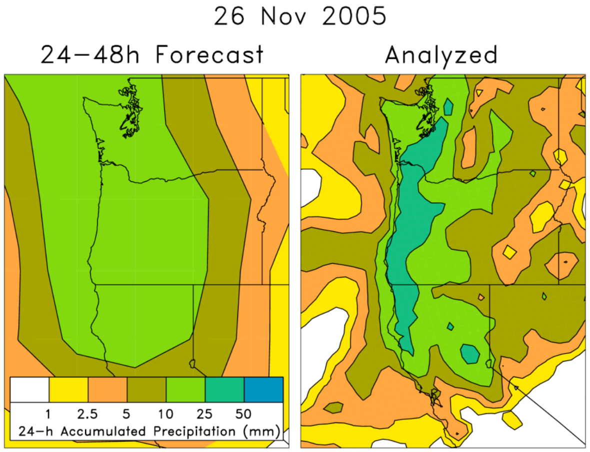
IMPROVING MONSOON MODELING
LOW-LEVEL JET CAMPAIGN
REFORECASTING
IMPROVING SKILL USING RETROSPECTIVE FORECASTS

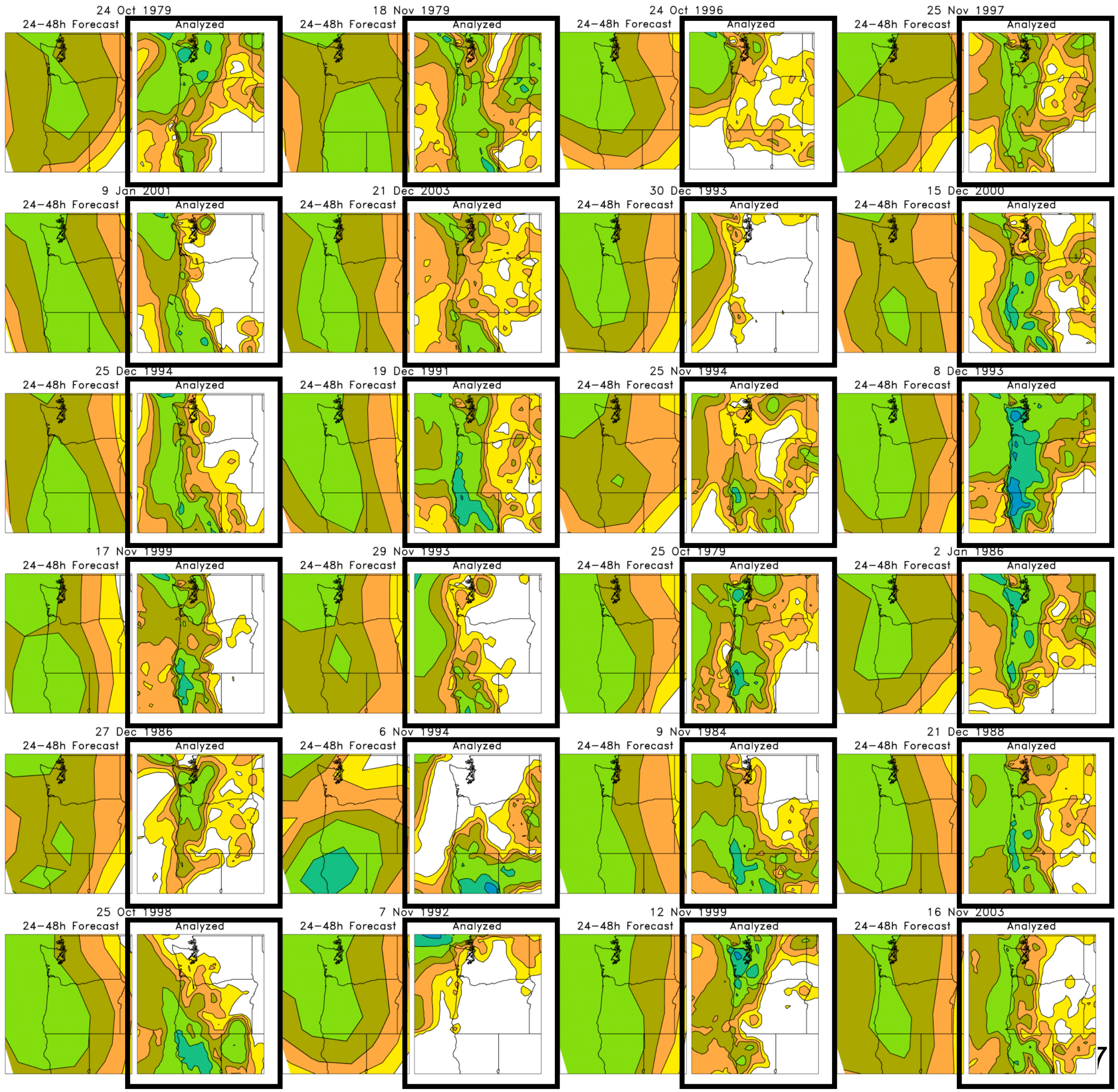
NOAA's reforecast data set

- **Model**: T62L28 NCEP GFS, circa 1998
- **Initial States**: NCEP-NCAR Reanalysis II plus 7 +/- bred modes.
- **Duration**: 15 days runs every day at 00Z from 19781101 to now. (*http://www.cdc.noaa.gov/people/jeffrey.s.whitaker/refcst/week2*).
- **Data**: Selected fields (winds, hgt, temp on 5 press levels, precip, t2m, u10m, v10m, pwat, prmsl, rh700, heating). NCEP/NCAR reanalysis verifying fields included (Web form to download at *http://www.cdc.noaa.gov/reforecast*). Data saved on 2.5-degree grid.
- **Experimental precipitation forecast products**: http://www.cdc.noaa.gov/reforecast/narr .

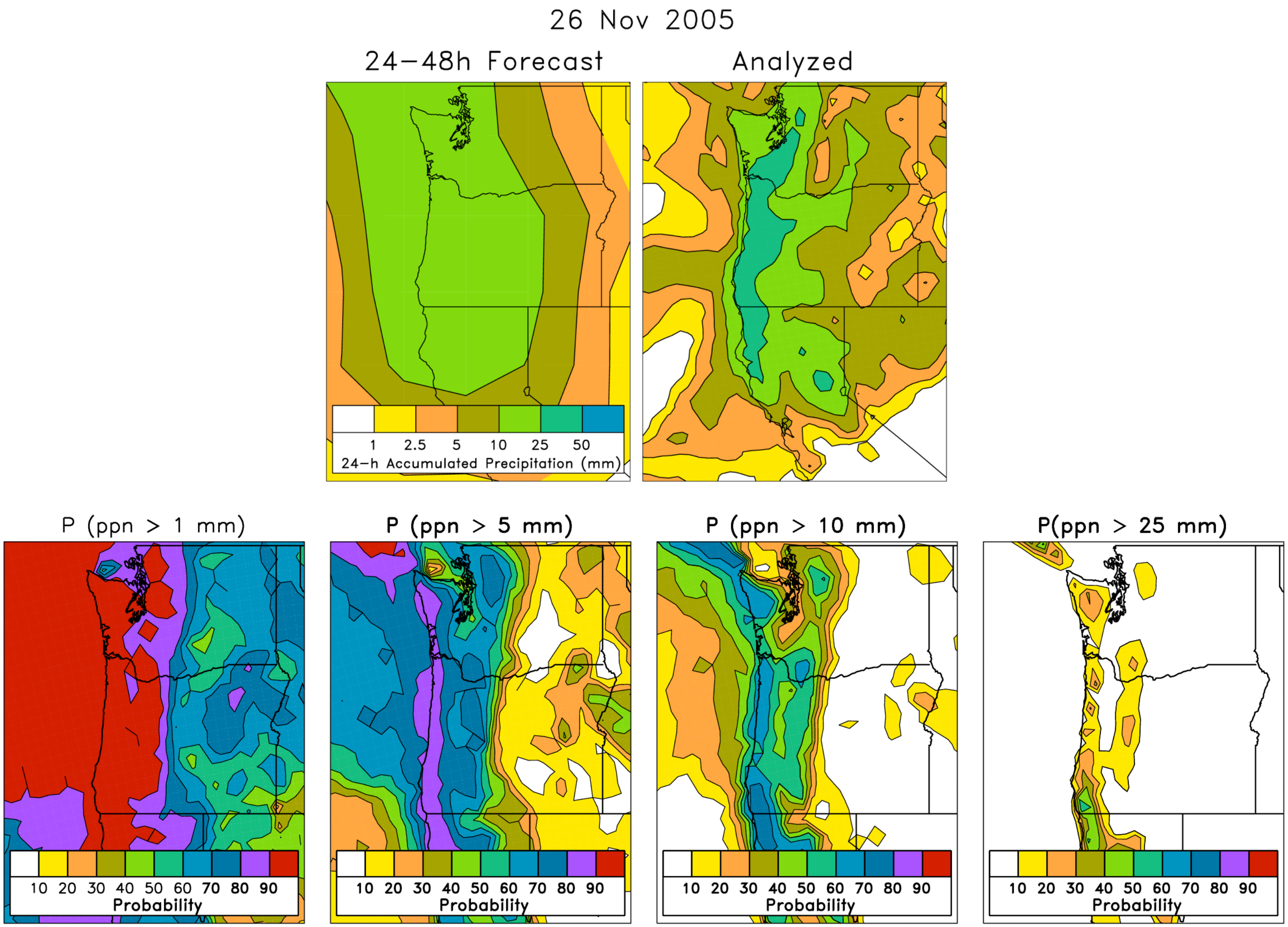
Reforecasts provide lots of old cases for diagnosing and correcting forecast errors.

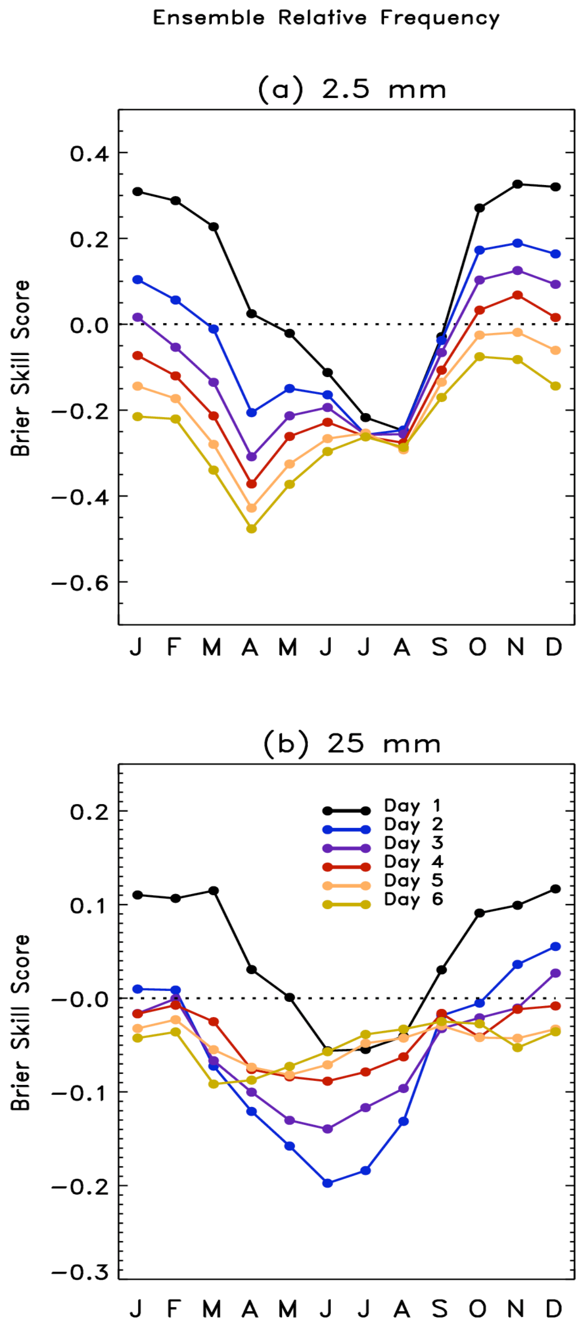


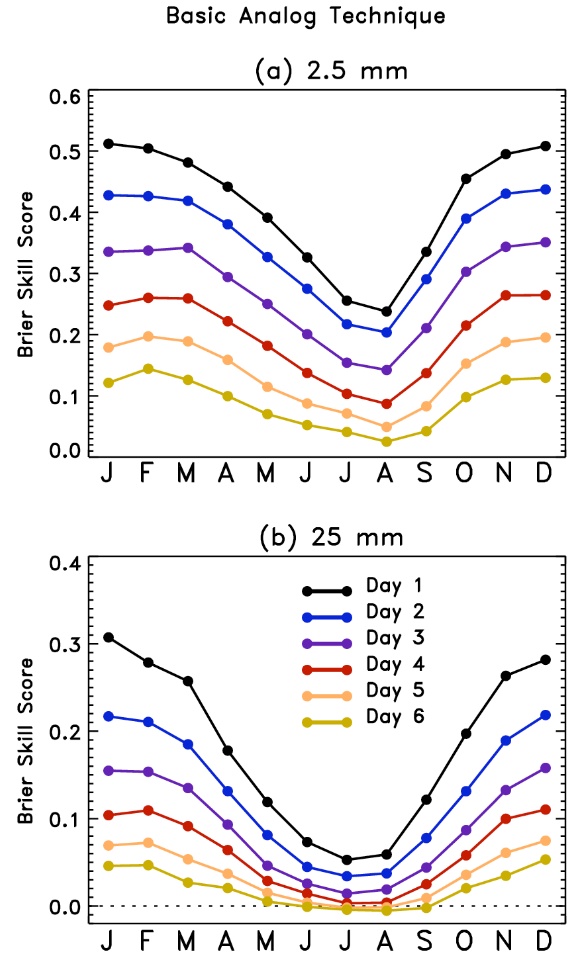
On the left are old forecasts similar to today's ensemble-mean forecast. The data on the right, the analyzed precipitation conditional upon the forecast, can be used to statistically adjust and downscale the forecast.



Downscaled analog probability forecasts







Example of the benefit of reforecasts

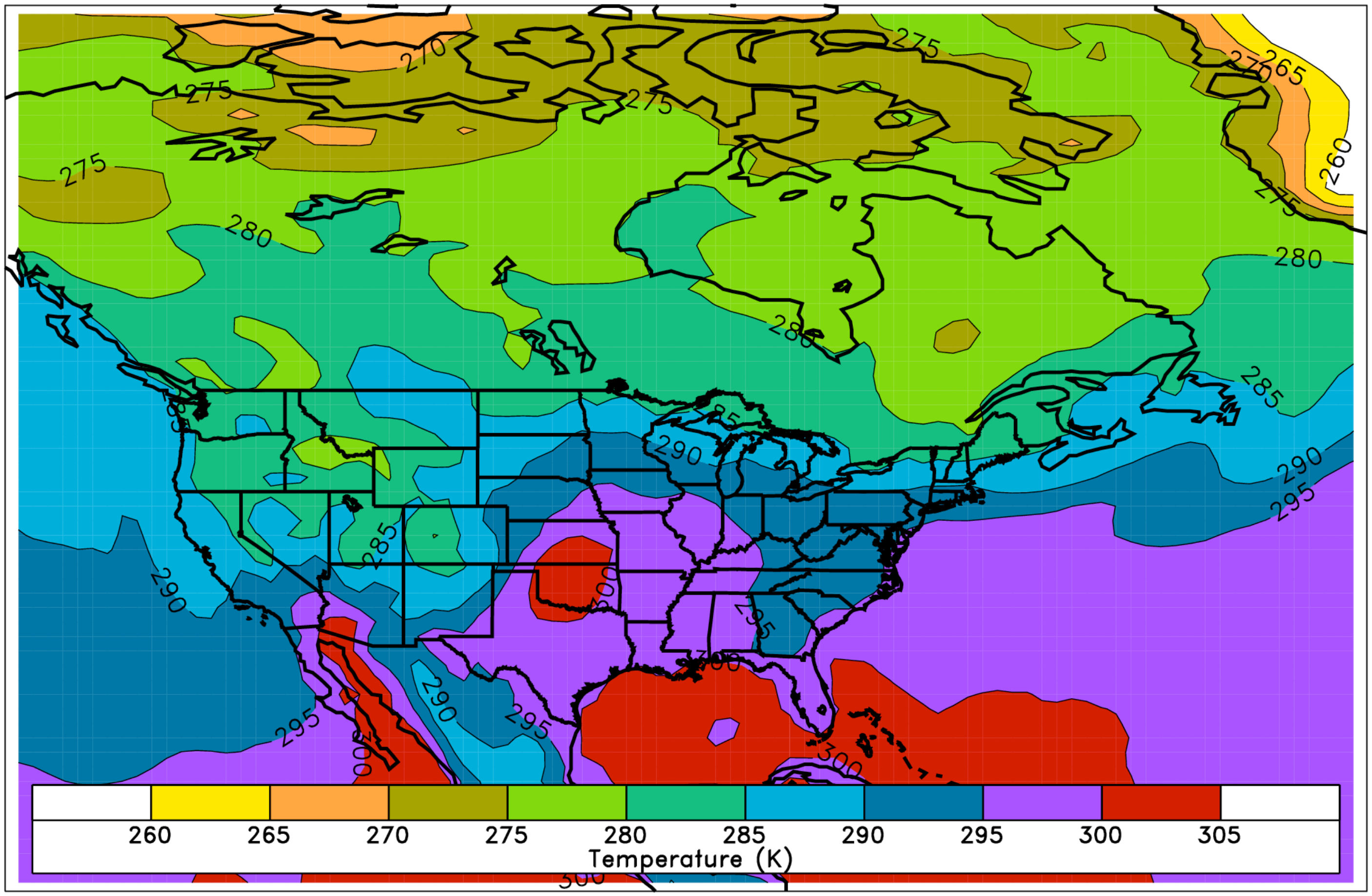
Verified over 25 years of forecasts; skill scores use conventional method of calculation which may overestimate skill (Hamill and Juras 2006).

ECMWF's reforecast data set

- **Model**: 2005 version of ECMWF model; T255 resolution.
- **Initial Conditions**: 15 members, ERA-40 analysis + singular vectors
- **Dates of reforecasts**: 1982-2001, Once-weekly reforecasts from 01 Sep - 01 Dec, 14 weeks total. So, 20y × 14w ensemble reforecasts = 280 samples.
- **Data** obtained by NOAA / ESRL : T_{2M} and precipitation ensemble over most of North America, excluding Alaska. Saved on 1-degree lat / lon grid. Forecasts to 10 days lead.

ECMWF domain sent to us for reforecast tests

Sample ECMWF 2–m temperature



Questions

- Will reforecasts benefit calibration of a state-of-the art model like ECMWF’s as much as with now outdated GFS model?
- How do probabilistic forecasts from the old GFS, with calibration, compare to the new ECMWF without?
- Are multi-decadal reforecasts really necessary? Given the computational expense of computing them, are much smaller training data sets adequate for probabilistic forecast calibration?

Outline

- A quick detour: examining why forecast skill metrics overestimate skill, and a proposed alternative.
- Calibrating temperature forecasts
- Calibrating precipitation forecasts
- Will reforecasting become operational at NWP centers worldwide?

Overestimating skill: a review of the Brier Skill Score

Brier Score: Mean-squared error of probabilistic forecasts.

$$\overline{BS}^{f} = \frac{1}{n}\sum_{k=1}^{n}\left(p_k^f - o_k\right)^2, \quad o_k = \begin{cases} 1.0 & if\ kth\ observation \geq threshold \\ 0.0 & if\ kth\ observation < threshold \end{cases}$$

Brier Skill Score: Skill relative to some reference, like climatology.
1.0 = perfect forecast, 0.0 = skill of reference.

$$BSS = \frac{\overline{BS}^{f} - \overline{BS}^{ref}}{\overline{BS}^{perfect} - \overline{BS}^{ref}} = \frac{\overline{BS}^{f} - \overline{BS}^{ref}}{0.0 - \overline{BS}^{ref}} = 1.0 - \frac{\overline{BS}^{f}}{\overline{BS}^{ref}}$$

Overestimating skill: example

<u>5-mm threshold</u>

Location A: $P^f = 0.05$, $P^{clim} = 0.05$, Obs = 0

$$BSS = 1.0 - \frac{\overline{BS}^f}{\overline{BS}^{clim}} = 1.0 - \frac{(.05-0)^2}{(.05-0)^2} = 0.0$$

Location B: $P^f = 0.05$, $P^{clim} = 0.25$, Obs = 0

$$BSS = 1.0 - \frac{\overline{BS}^f}{\overline{BS}^{clim}} = 1.0 - \frac{(.05-0)^2}{(.25-0)^2} = 0.96$$

Locations A and B:

$$BSS = 1.0 - \frac{\overline{BS}^f}{\overline{BS}^{clim}} = 1.0 - \frac{(.05-0)^2 + (.05-0)^2}{(.25-0)^2 + (.05-0)^2} = 0.923$$

Overestimating skill: another example

5-mm threshold

Location A: $P^f = 0.05$, $P^{clim} = 0.05$, Obs = 0

$$BSS = 1.0 - \frac{\overline{BS}^f}{\overline{BS}^{clim}} = 1.0 - \frac{(.05-0)^2}{(.05-0)^2} = 0.0$$

Location B: $P^f = 0.05$, $P^{clim} = 0.25$, Obs = 0

$$BSS = 1.0 - \frac{\overline{BS}^f}{\overline{BS}^{clim}} = 1.0 - \frac{(.05-0)^2}{(.25-0)^2} = 0.96$$

Locations A and B:

$$BSS = 1.0 - \frac{\overline{BS}^f}{\overline{BS}^{clim}} = 1.0 - \frac{(.05-0)^2 + (.05-0)^2}{(.25-0)^2 + (.05-0)^2} = 0.923$$

why not 0.48?

for more detail, see Hamill and Juras, QJRMS, Oct 2006 (c)

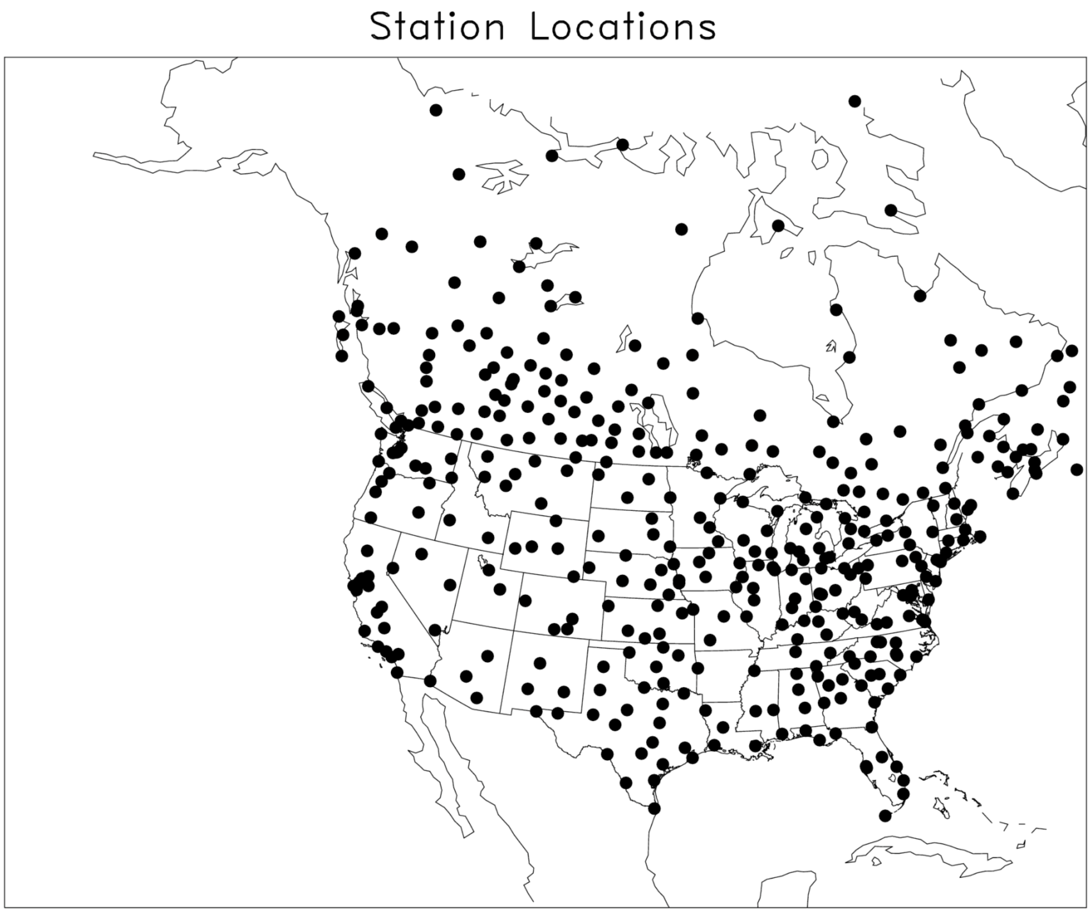
An alternative *BSS*

Say *m* overall samples, and *k* categories where climatological event probabilities are similar in this category. $n_s(k)$ samples assigned to this category. Then form BSS from weighted average of skills in the categories.

$$BSS = \sum_{k=1}^{n_c} \frac{n_s(k)}{m} \left(1 - \frac{\overline{BS}^f(k)}{\overline{BS}^{clim}(k)} \right)$$

(for more details on all of this, see Hamill and Juras, *QJRMS*, October C, 2006)

Observation locations for temperature calibration



Produce probabilistic forecasts at stations.

Use stations from NCAR's DS472.0 database that have more than 96% of the yearly records available, and overlap with the domain that ECMWF sent us.

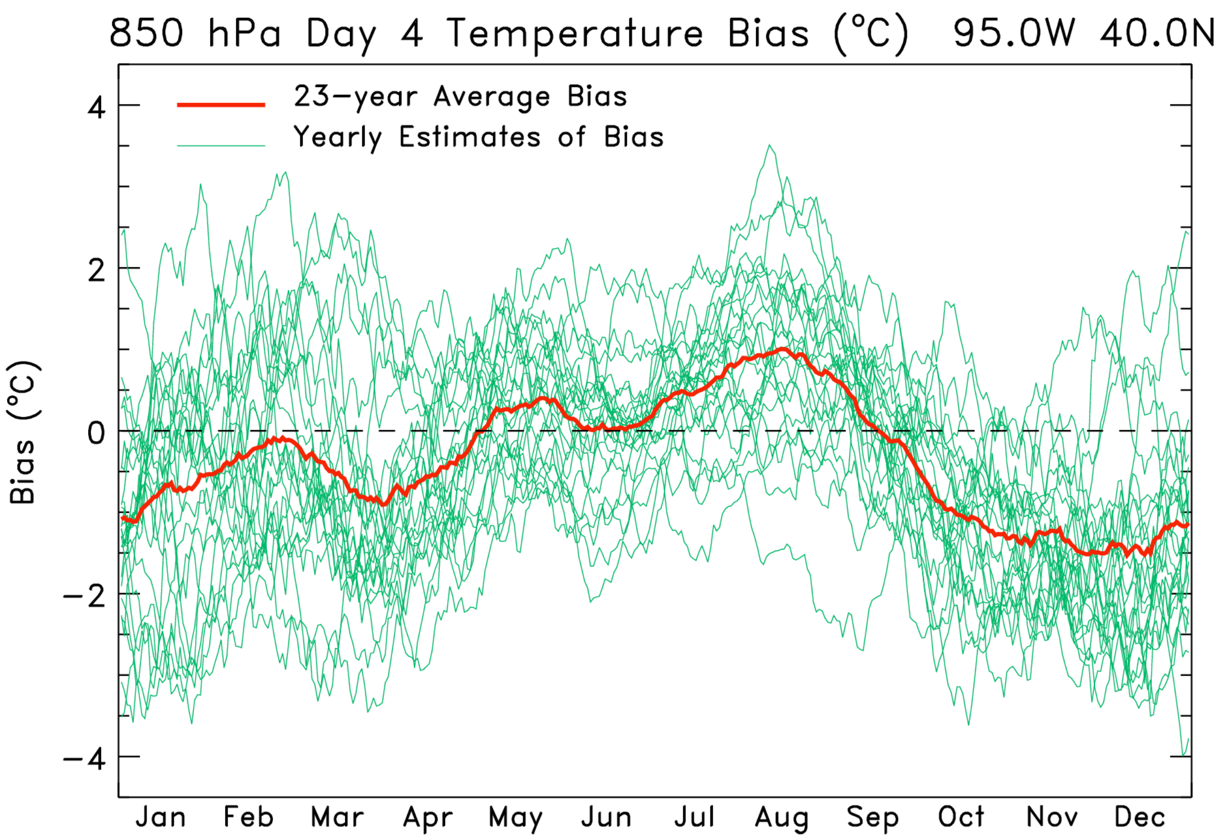
Calibration Procedure: "NGR"
"Non-homogeneous Gaussian Regression"

- **Reference**: Gneiting et al., *MWR*, **133**, p. 1098. Shown in Wilks and Hamill (MWR, 135, p 2379) to be best of common calibration methods for surface temperature using reforecasts.
- **Predictors**: ensemble mean and ensemble spread
- **Output**: mean, spread of calibrated normal distribution

$$f^{CAL}\left(\overline{\mathbf{x}}, \sigma\right) \sim N\left(a + b\overline{\mathbf{x}}, c + d\sigma\right)$$

- **Advantage**: leverages possible spread/skill relationship appropriately. Large spread/skill relationship, c ≈ 0.0, *d* ≈1.0. Small, *d* ≈ 0.0
- **Disadvantage**: iterative method, slow…no reason to bother (relative to using simple linear regression) if there's little or no spread-skill relationship.

Inter-annual variability of forecast bias

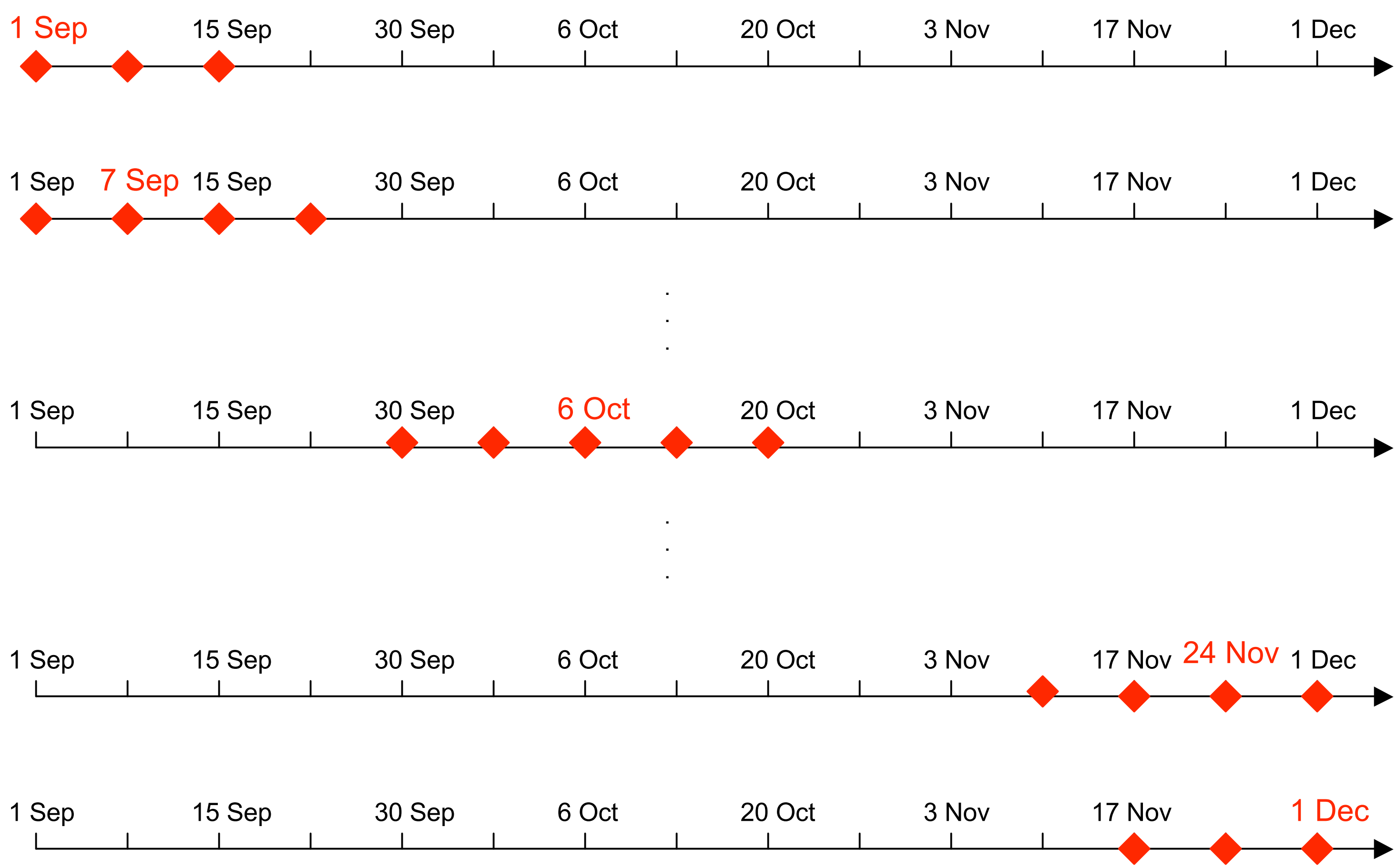


Red curve shows bias averaged over 23 years of data (bias = mean F-O in running 61-day window)

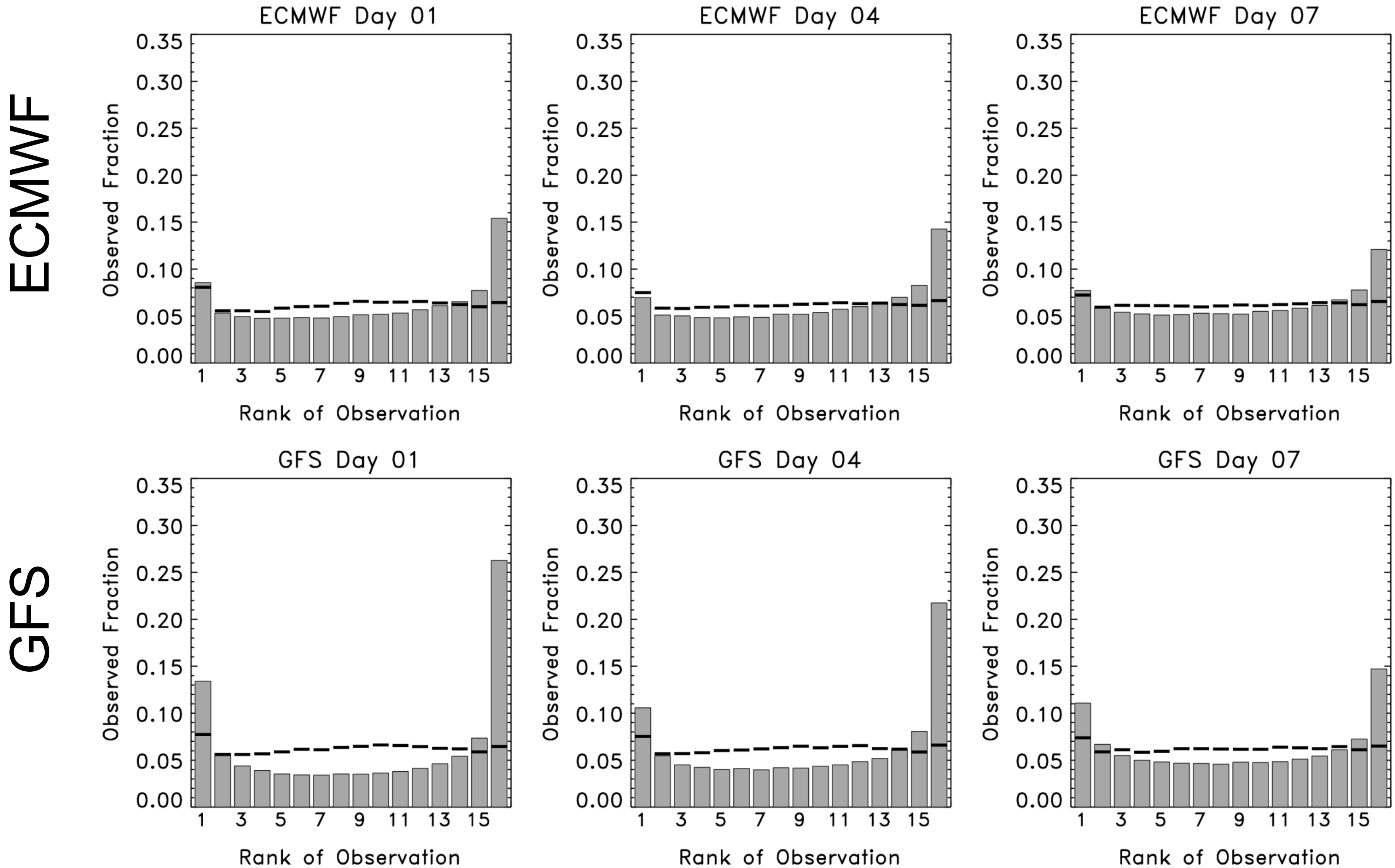
Green curves show 23 individual yearly running-mean bias estimates

Note large inter-annual variability of bias.

What training data to use, given inter-annual variability of bias?

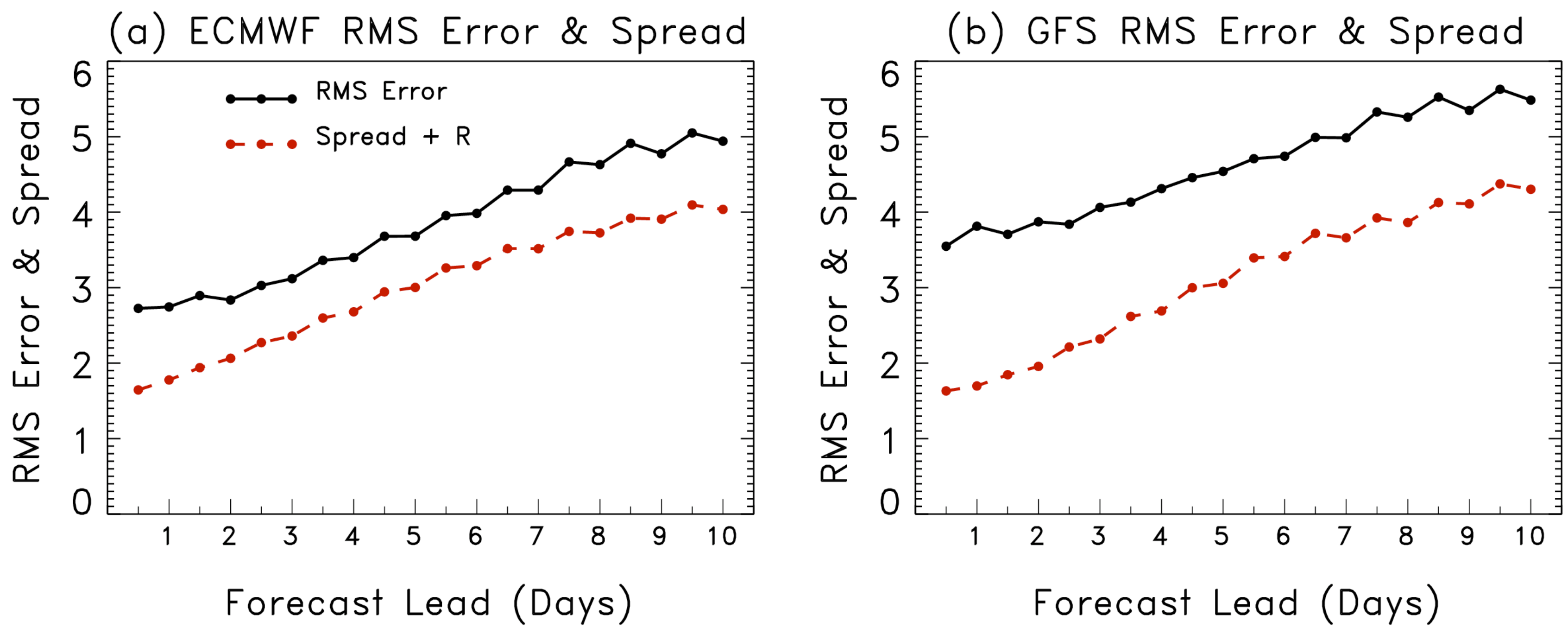


Rank histograms



Members randomly perturbed by 1.5K to account for observation error; probably a bit small for GFS on its coarser 2.5^o grid, which would make their histograms slightly more uniform. Ref: Hamill, *MWR*, **129**, p. 556. Solid lines for after calibration

Forecast spread and error



For both systems, with 2-m temperature, there is a deficiency of spread. This is much worse for GFS than ECMWF.

Continuous Ranked Probability Score (CRPS) and Skill Score (CRPSS)

$$CRPS^f_{i,j,k} = \int_{-\infty}^{+\infty} \left[F_{i,j,k}(y) - F^o_{i,j,k}(y) \right]^2 dy$$

$$i = 1, \ldots, \# \; case \; days$$

$$j = 1, \ldots, \# \; years \; of \; reforecasts$$

$$k = 1, \ldots, \# \; station \; locations$$

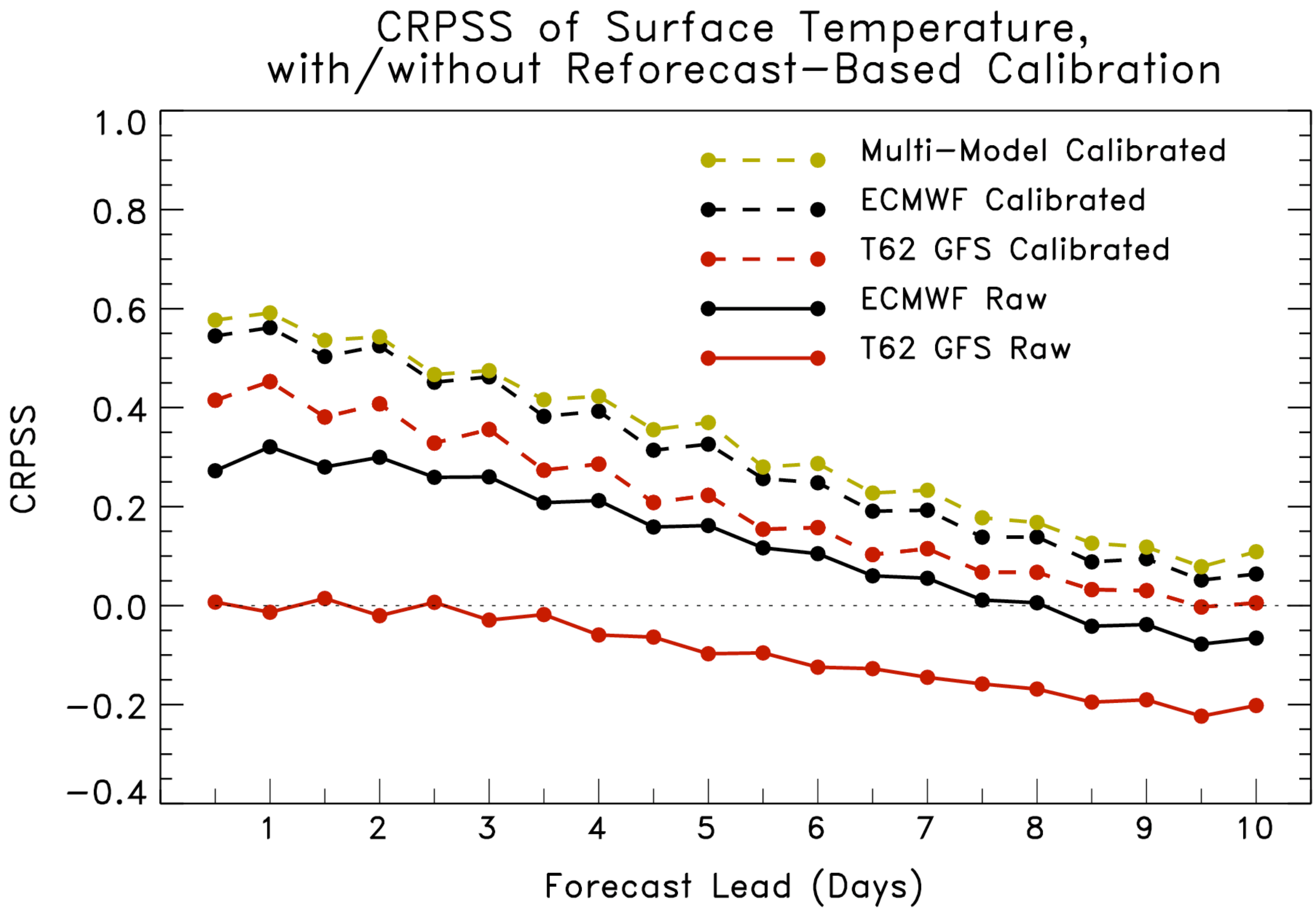
$$F_{i,j,k}(y) \; is \; forecast \; CDF \; at \; value \; y$$

$$F^o_{i,j,k}(y) \; is \; obs \; CDF \; at \; value \; y \; (Heaviside)$$

$$CRPSS = 1.0 - \frac{\overline{CRPS}^f}{\overline{CRPS}^c}$$

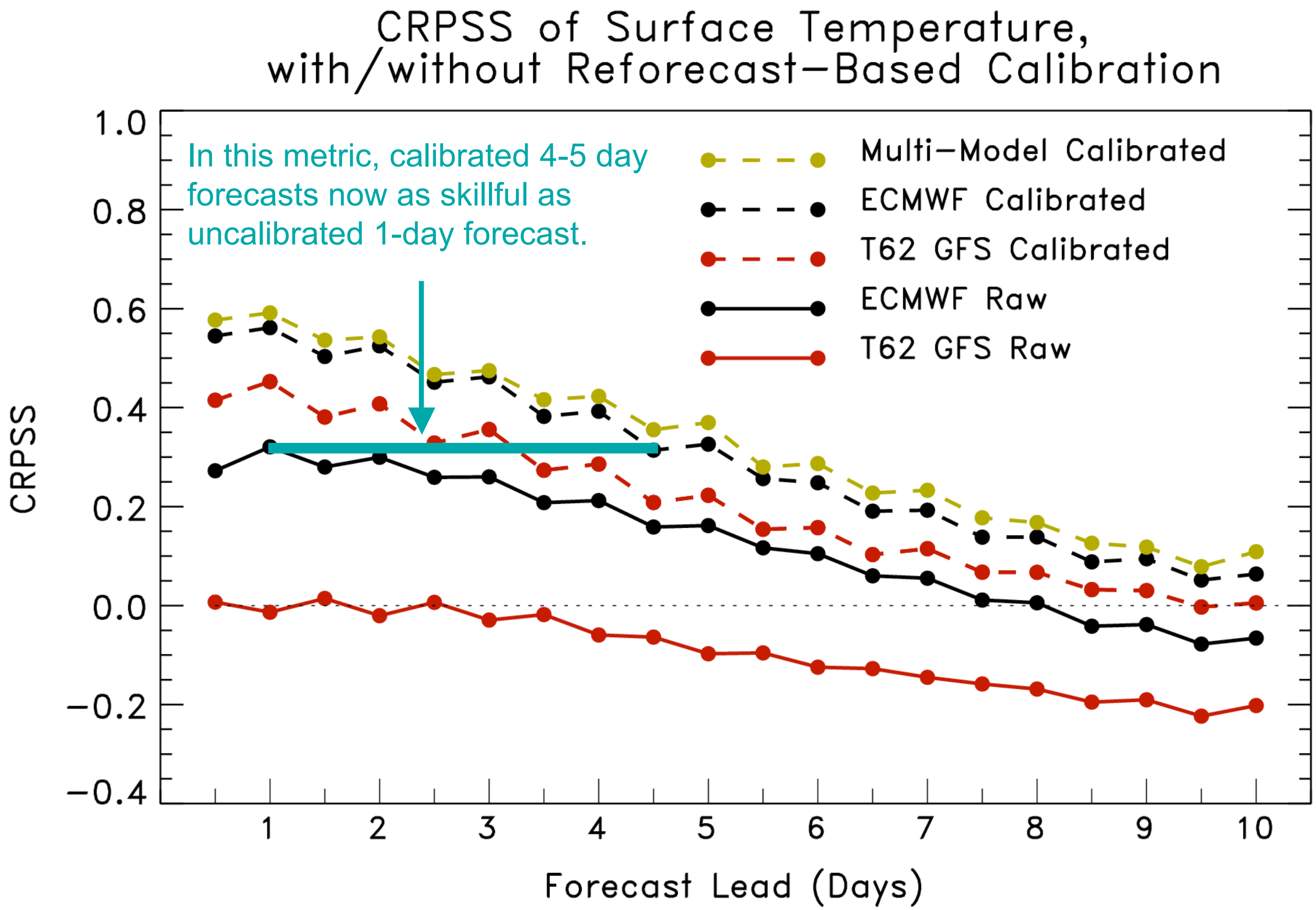
Will use a modified version where we calculate CRPSS separately for 8 different categories of climatological spread and then average them. See Hamill and Juras, January 2007, *QJRMS,* and Hamill and Whitaker Sep. 2007 *MWR.*

ECMWF, raw and post-processed



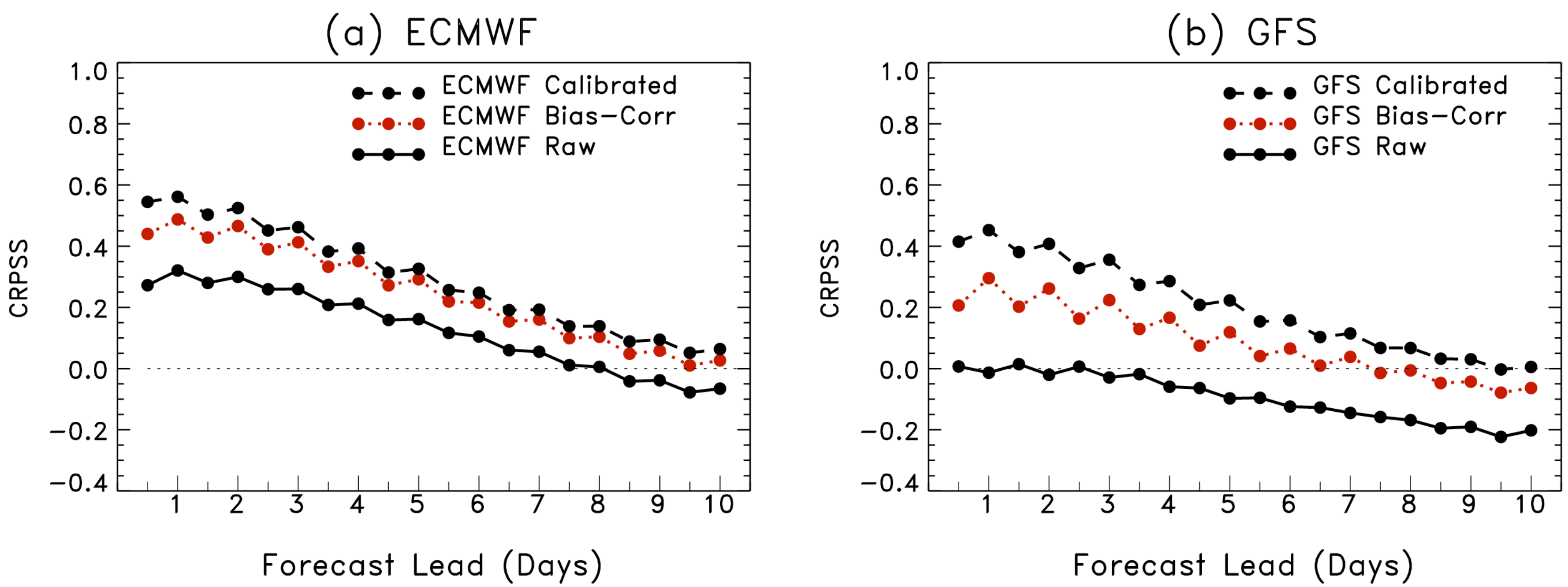
Note: 5th and 95th %ile confidence intervals very small, 0.02 or less

ECMWF, raw and post-processed

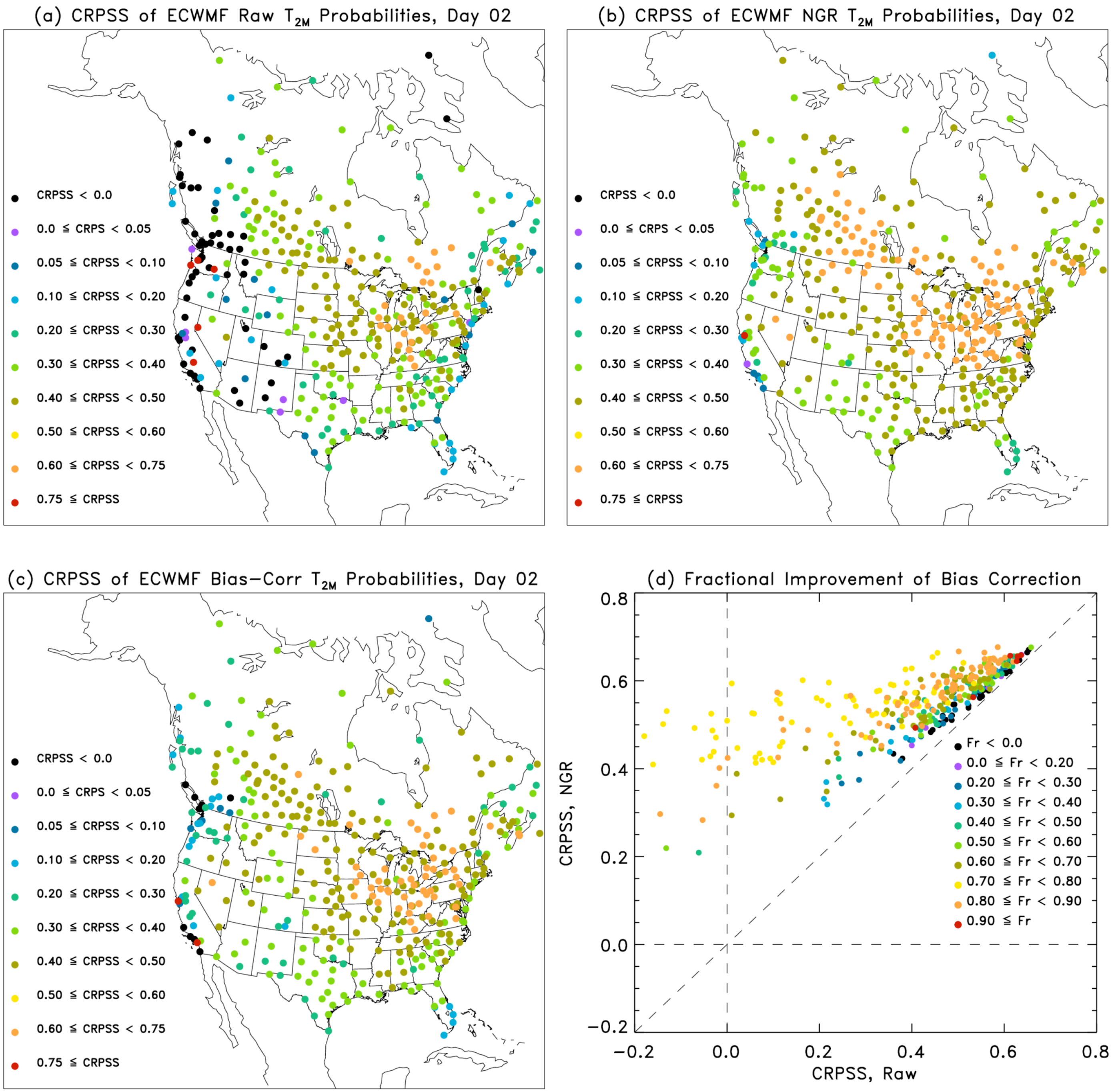


Note: 5th and 95th %ile confidence intervals very small, 0.02 or less

How much from simple bias correction?



~ 60 percent of total improvement at short leads, 70 percent at longer leads.

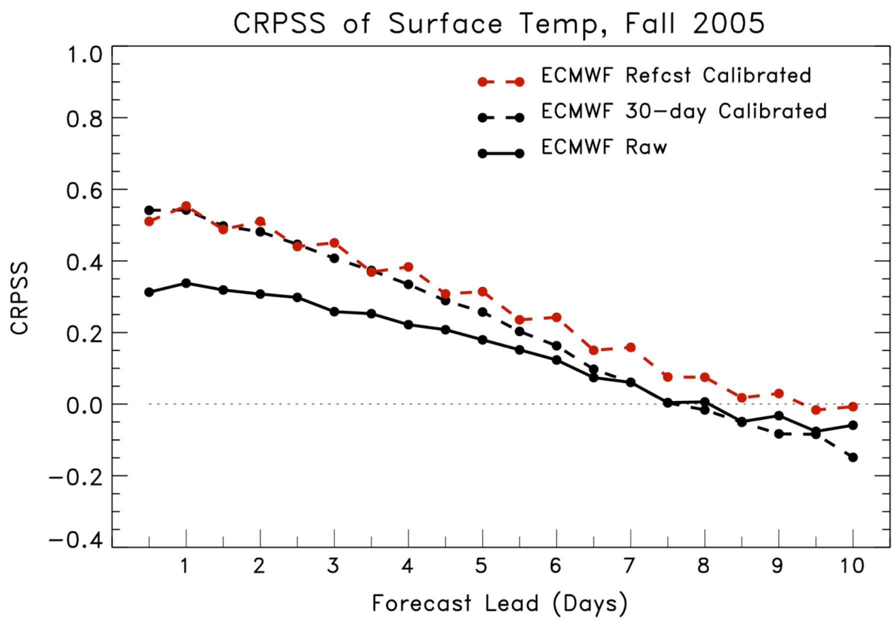


ECMWF’s geographical distribution of skill, before and after calibration.

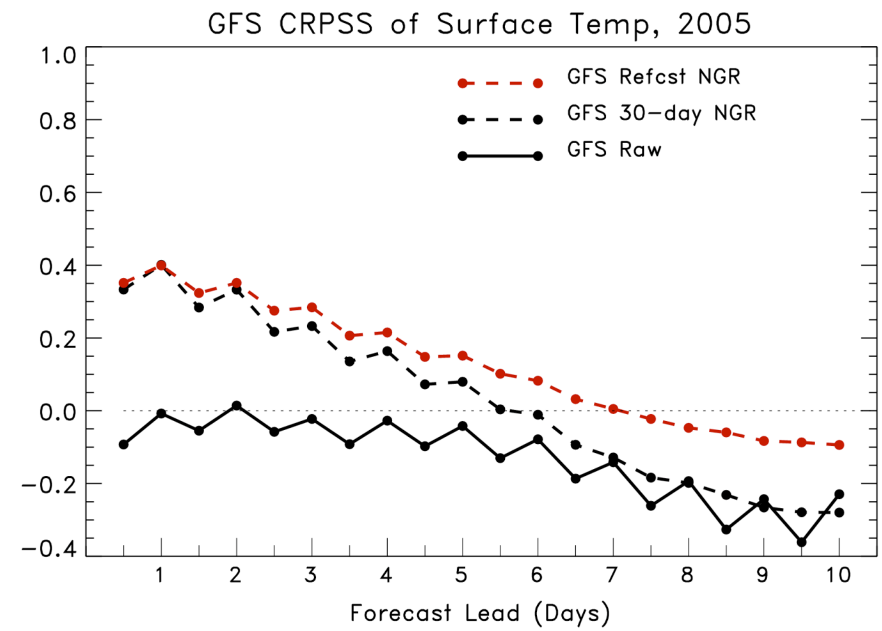
The tide of calibration raises all boats, the sunken ones the most.

How much from short training data sets?

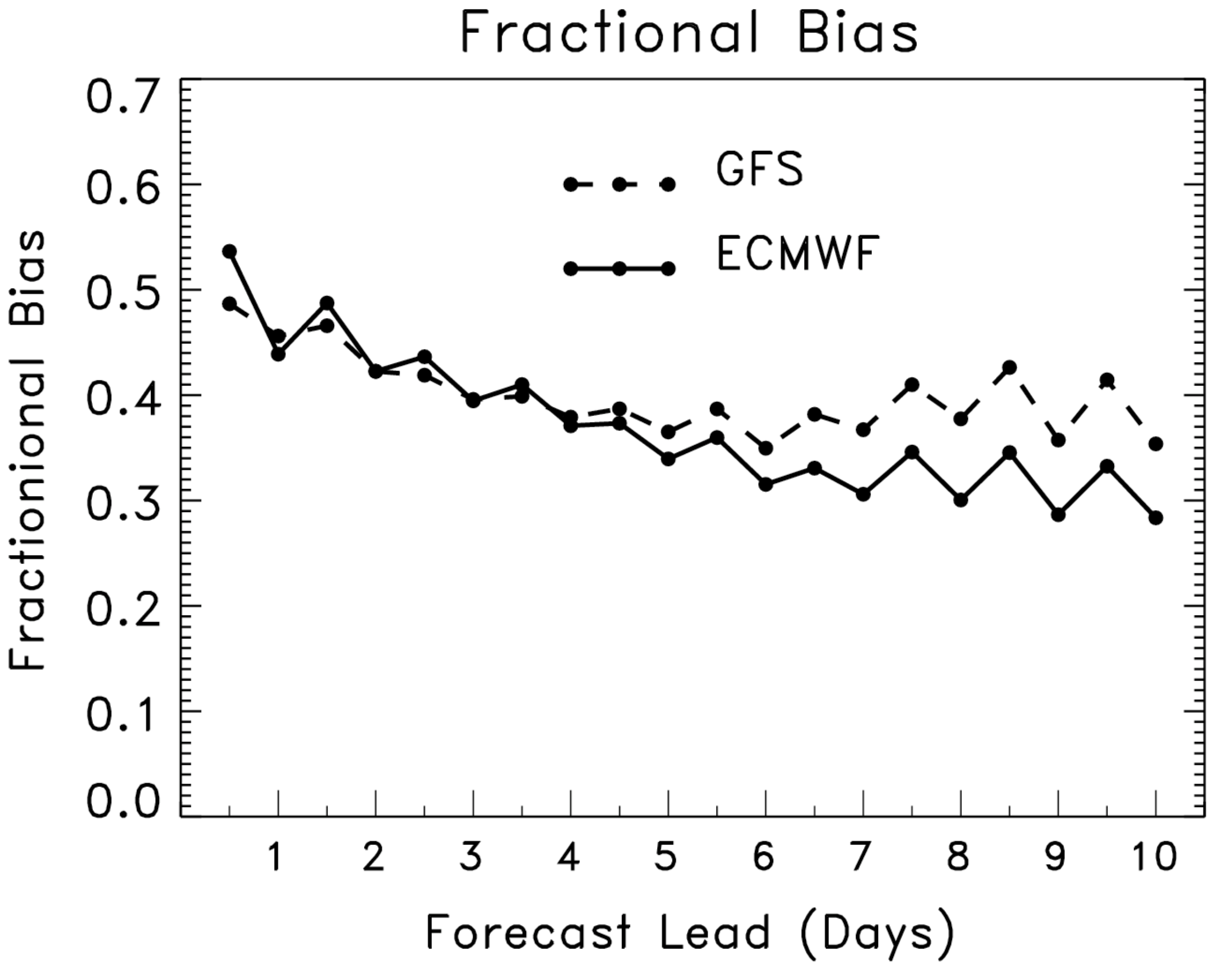
ECMWF



GFS

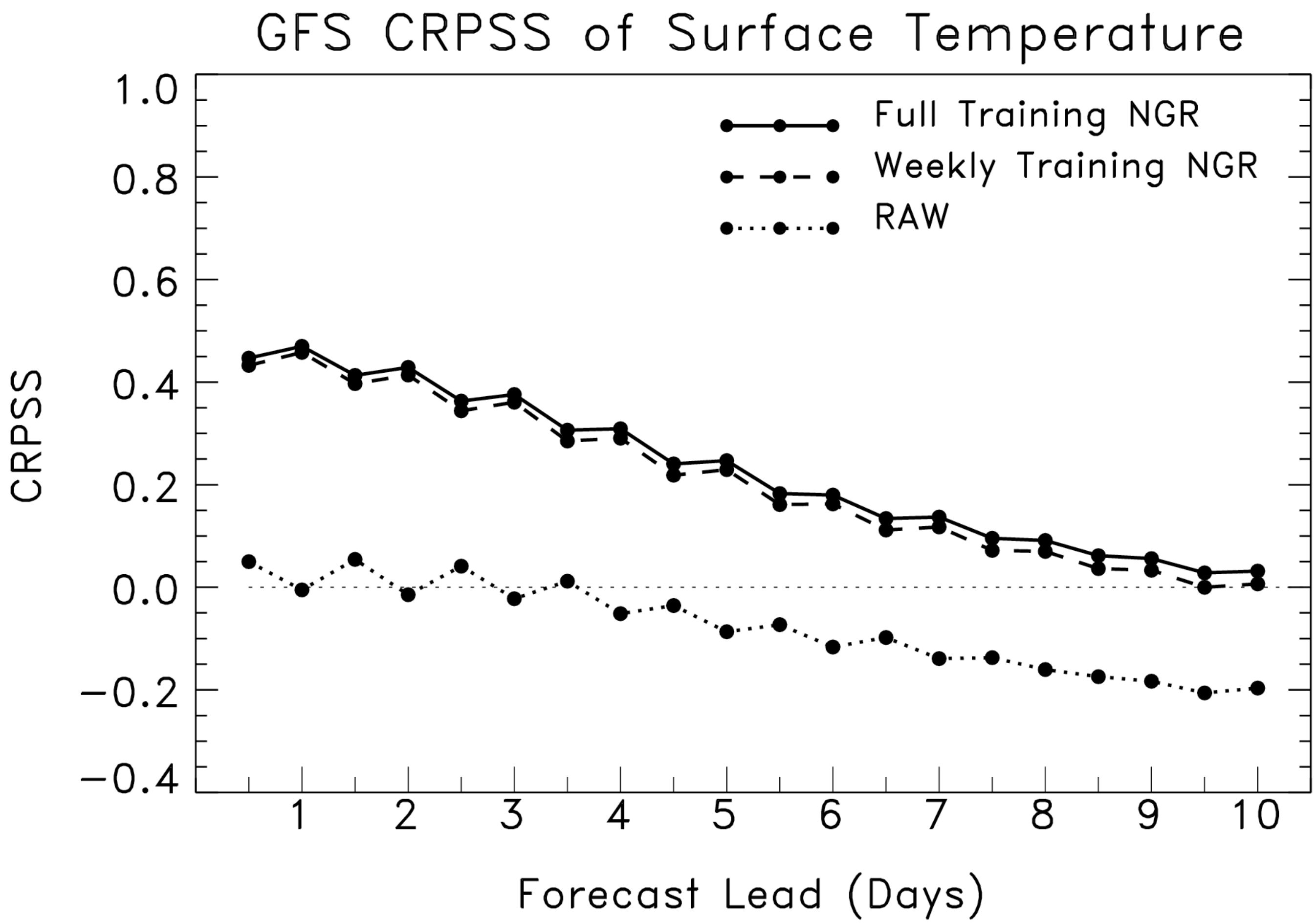


Note: (1) that ECMWF reforecasts use 3D-Var initial condition, 2005 real-time forecasts use 4D-Var. This difference may lower skill with reforecast training data set. (2) No other predictors besides forecast T2m; perhaps with, say, soil moisture as additional predictor, reforecast calibration would improve relative to 30-day.



This measures the percentage of the forecast error that can be attributed to a long-term mean bias, as opposed to random errors due to chaos. Random errors are a larger percentage at long leads.

How much from long GFS training data set?



Here GFS reforecasts sampled once per week are compared to those sampled once per day ("full").

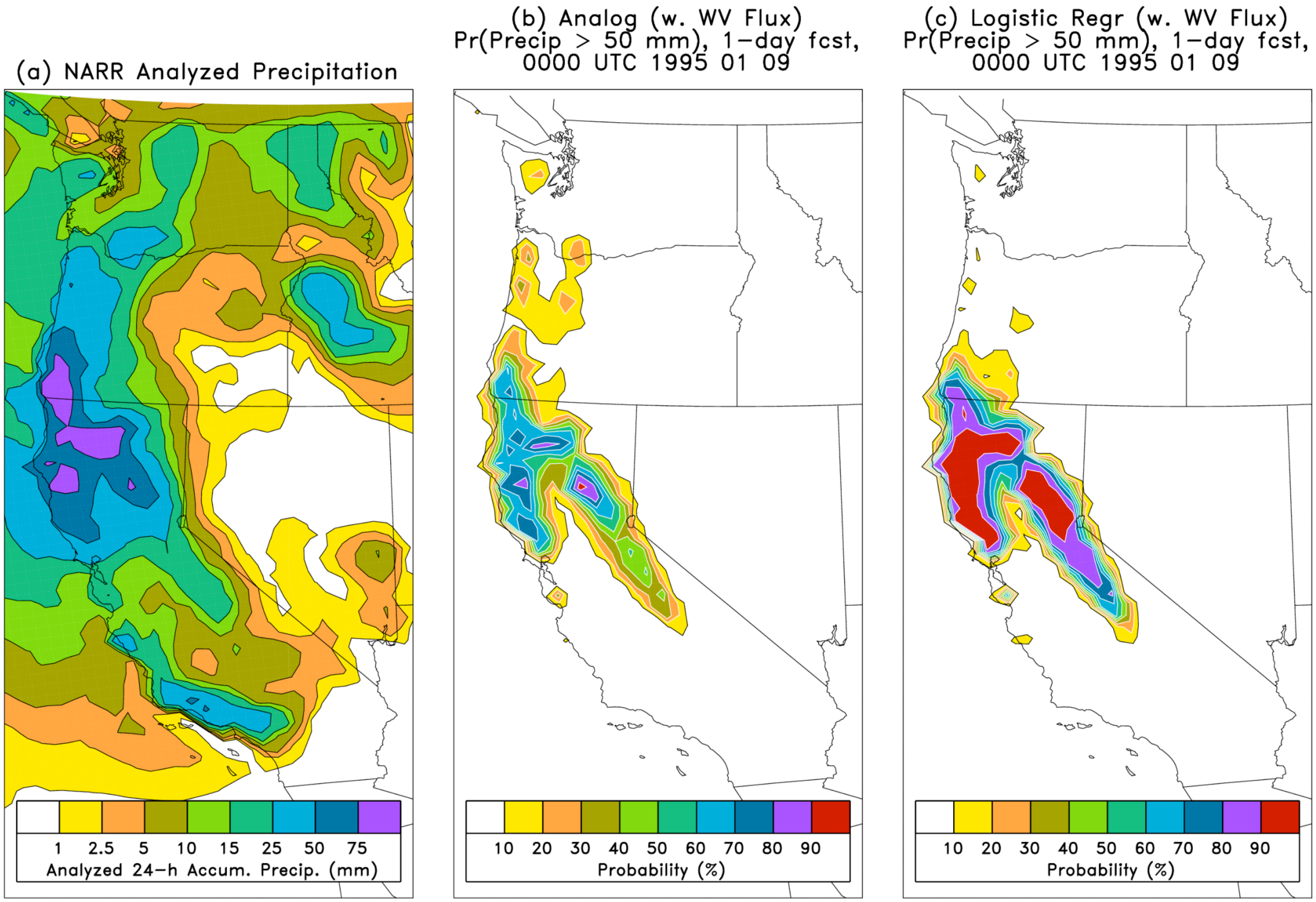
Precipitation calibration

- NARR CONUS 12-hourly data used for training, verification. ~32 km grid spacing
- Logistic regression for calibration here

$$P(O > T) = 1.0 - \frac{1.0}{1.0 + \exp\left\{\beta_0 + \beta_1\left(\overline{x}^f\right)^{0.25} + \beta_2\left(\sigma^f\right)^{0.25}\right\}}$$

- More weight to samples with heavier forecast precipitation to improve calibration for heavy-rain events.
- Unlike temperature, throw Sep-Dec training data together.

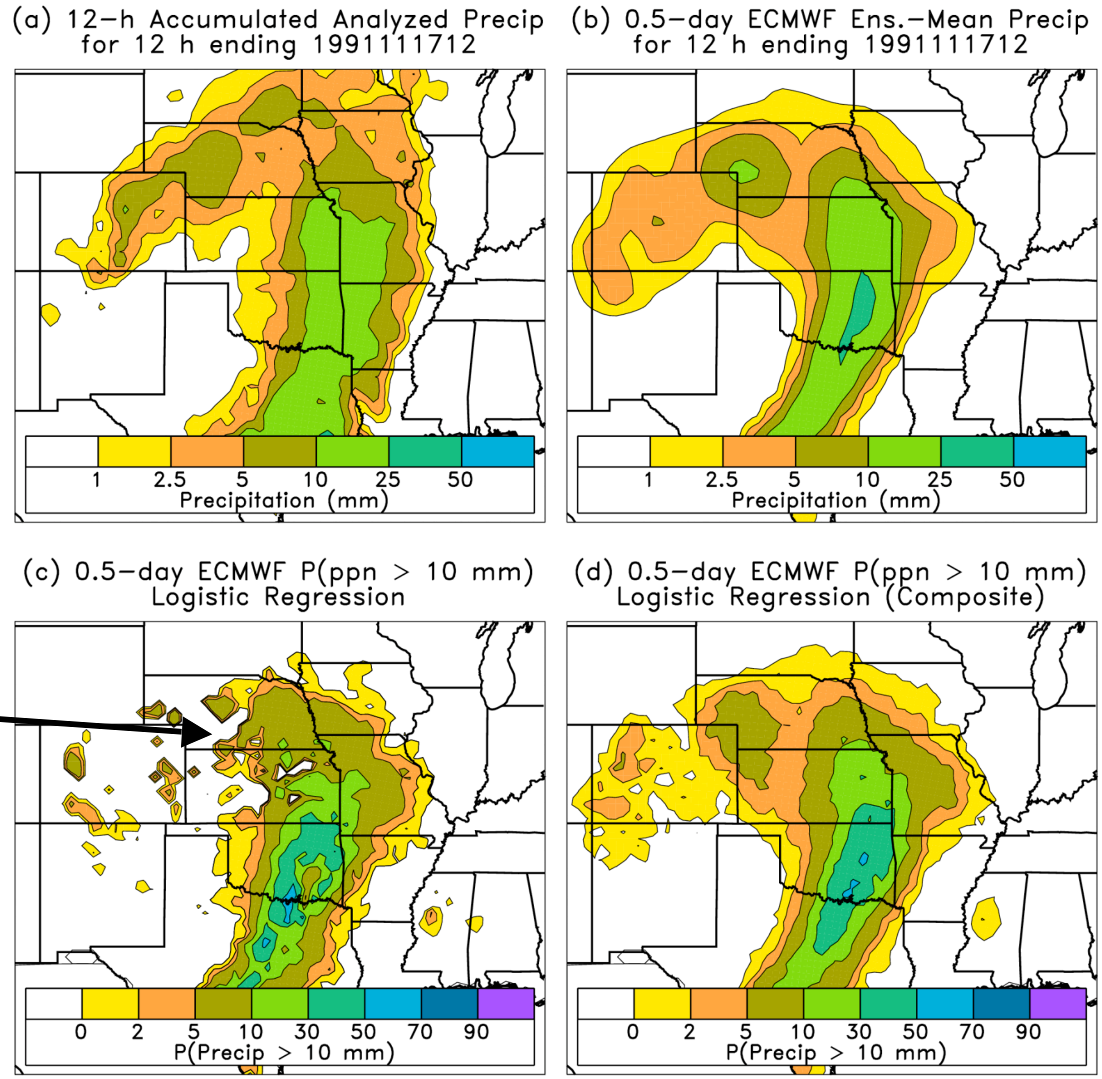
Logistic regression similar to analog …



…though it tends to forecast higher probabilities

Problem: patchy probabilities when grid point X trained with only grid point X's forecasts / obs

Even 20 years of weekly forecast data (260 samples after cross-validation) is not enough for stable regression coefficients, especially at higher precipitation thresholds.



When is it proper to use training data at location B to supplement regression analysis at location A?

(1) When location B's errors are independent of location A's errors.

(2) When observed CDF at A and B are very similar.

(3) When forecast CDF at A and B are very similar.

(4) When corr(forecast, observed) at A and B are similar.

When is it proper to use training data at location B to supplement regression analysis at location A?

(1) When location B's errors are independent of location A's errors.

Make sure location A is not too close to location B

(2) When observed CDF at A and B are very similar.

(3) When forecast CDF at A and B are very similar.

(4) When corr(forecast, observed) at A and B are similar.

When is it proper to use training data at location B to supplement regression analysis at location A?

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(4) When corr(forecast, observed) at A and B are similar.

Need lots of samples. Luckily, ~28 year NARR provides them.

When is it proper to use training data at location B to supplement regression analysis at location A?

(1) When location B’s errors are independent of location A’s errors.

(2) When observed CDF at A and B are very similar

(3) When forecast CDF at A and B are very similar.

(4) When corr(forecast, observed) at A and B are similar.

Judging this would be tough with ECMWF forecasts. Only 14 weeks*20 years, not a large sample for non-normally distributed data. Can be fooled by rare events.

When is it proper to use training data at location B to supplement regression analysis at location A?

(1) When location B's errors are independent of location A's errors.

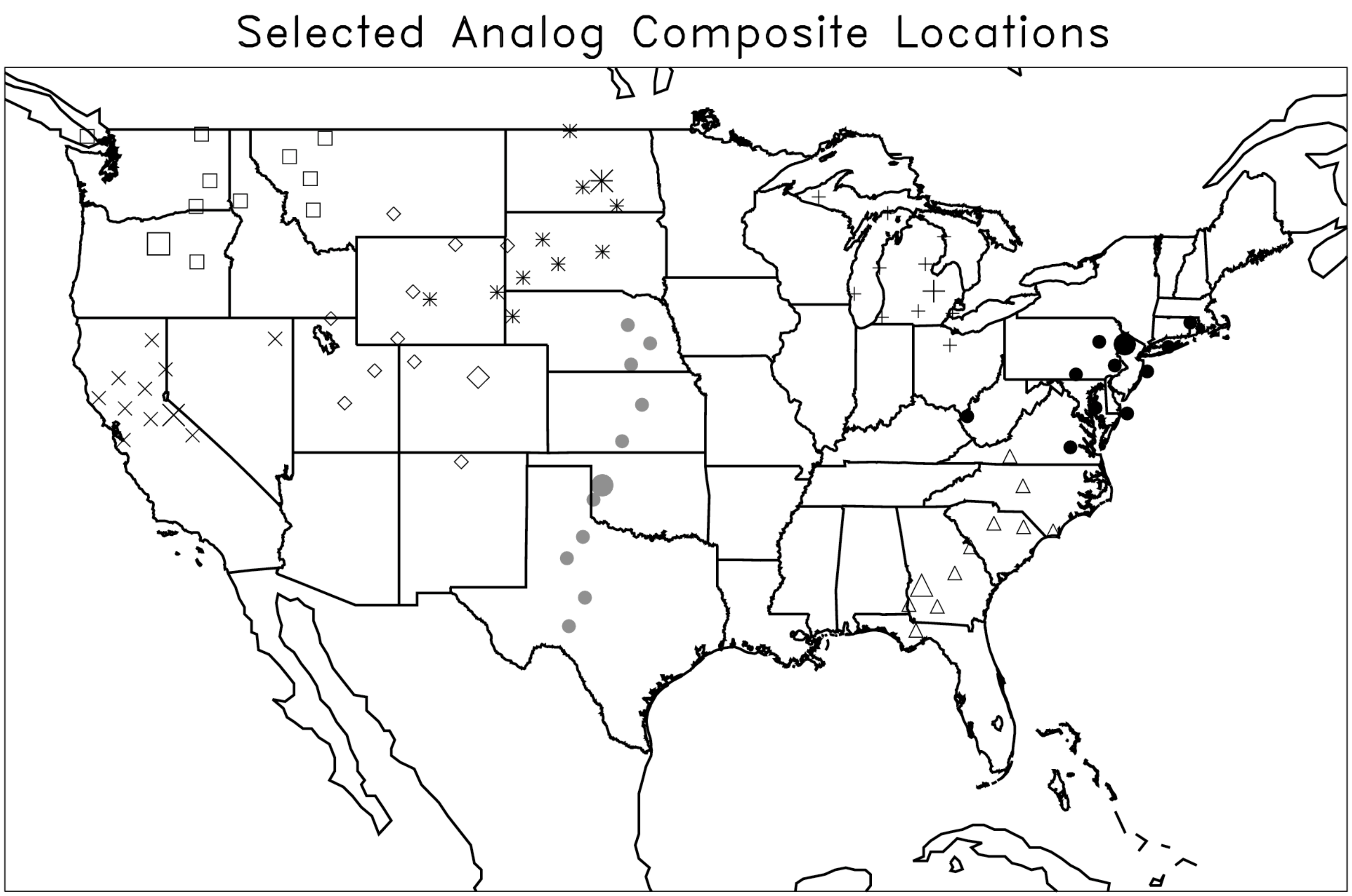
(2) When observed CDF at A and B are very similar

(3) When forecast CDF at A and B are very similar.

(4) When corr(forecast, observed) at A and B are similar.

Tricky to compute in dry regions, where overwhelming bulk of the samples are zero's.

Tested method: add in training data at other grid points that have similar analyzed climatologies



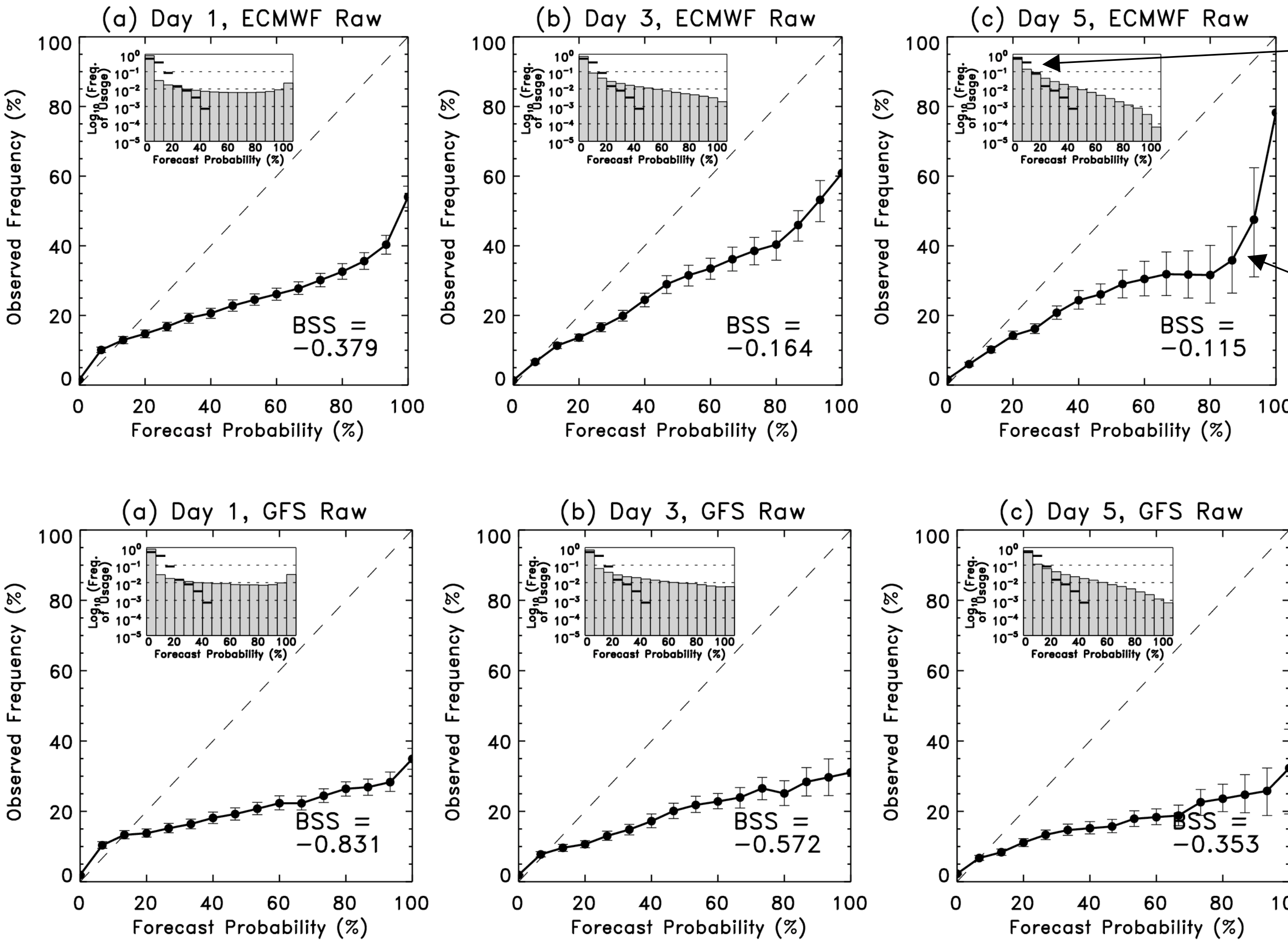
Big symbol:
grid point
where we
do regression

Small symbols:
analog locations
with similar
climatologies

Training data sets tested

- "Weekly" - use 1x weekly, 20-year reforecasts for training data. Sep-Dec cases all thrown together. X-validated.
- "30-day" - for 2005 only, where forecasts available every day, train using the prior available 30 days.
- "Full" (GFS only) - use 25 years of daily reforecasts. X-validated.

5-mm reliability diagrams, raw ensembles



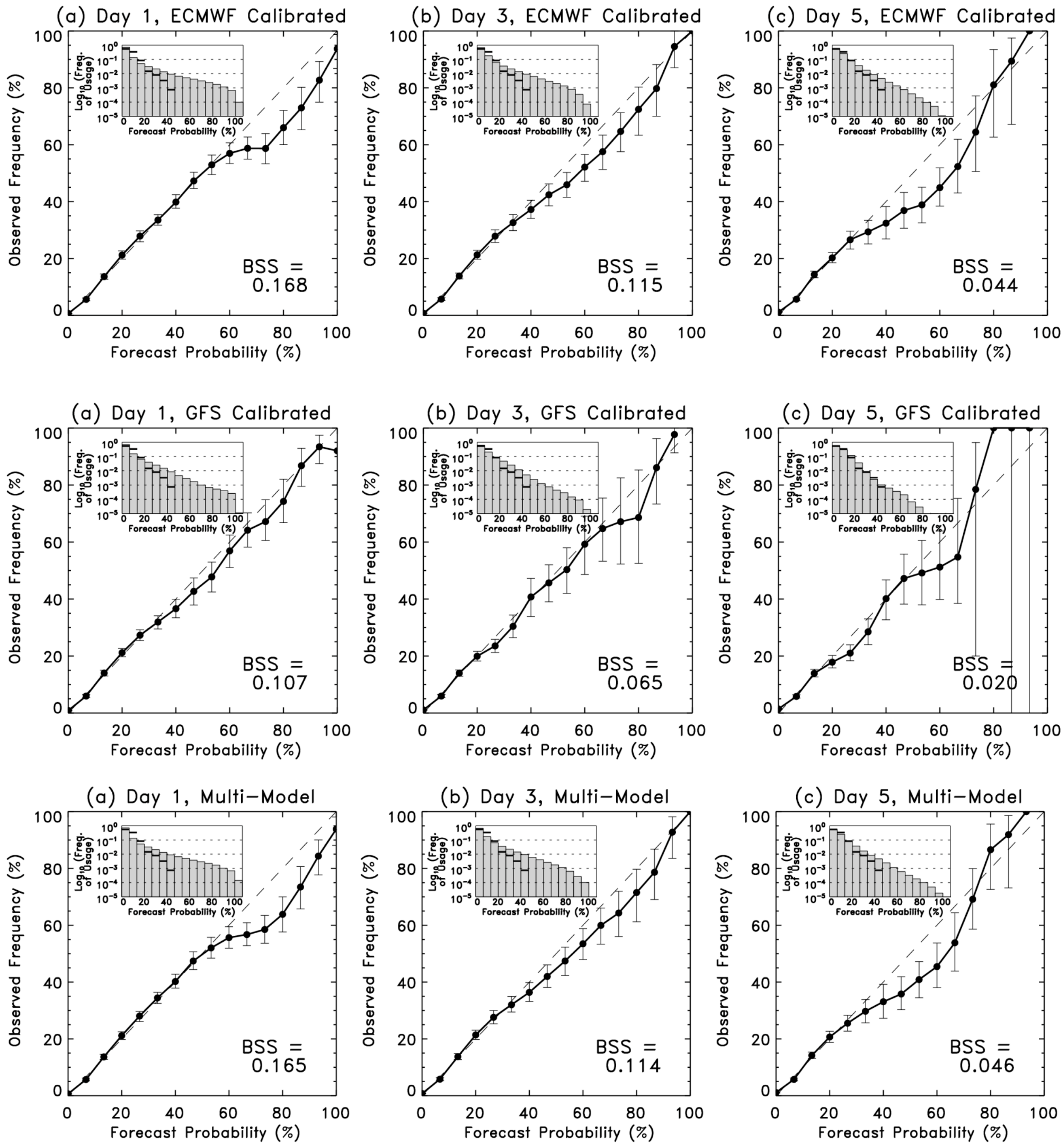
horizontal lines indicate distribution of climatology

error bars from block bootstrap

Raw forecasts have poor skill in this strict BSS

5-mm reliability diagrams, calibrated

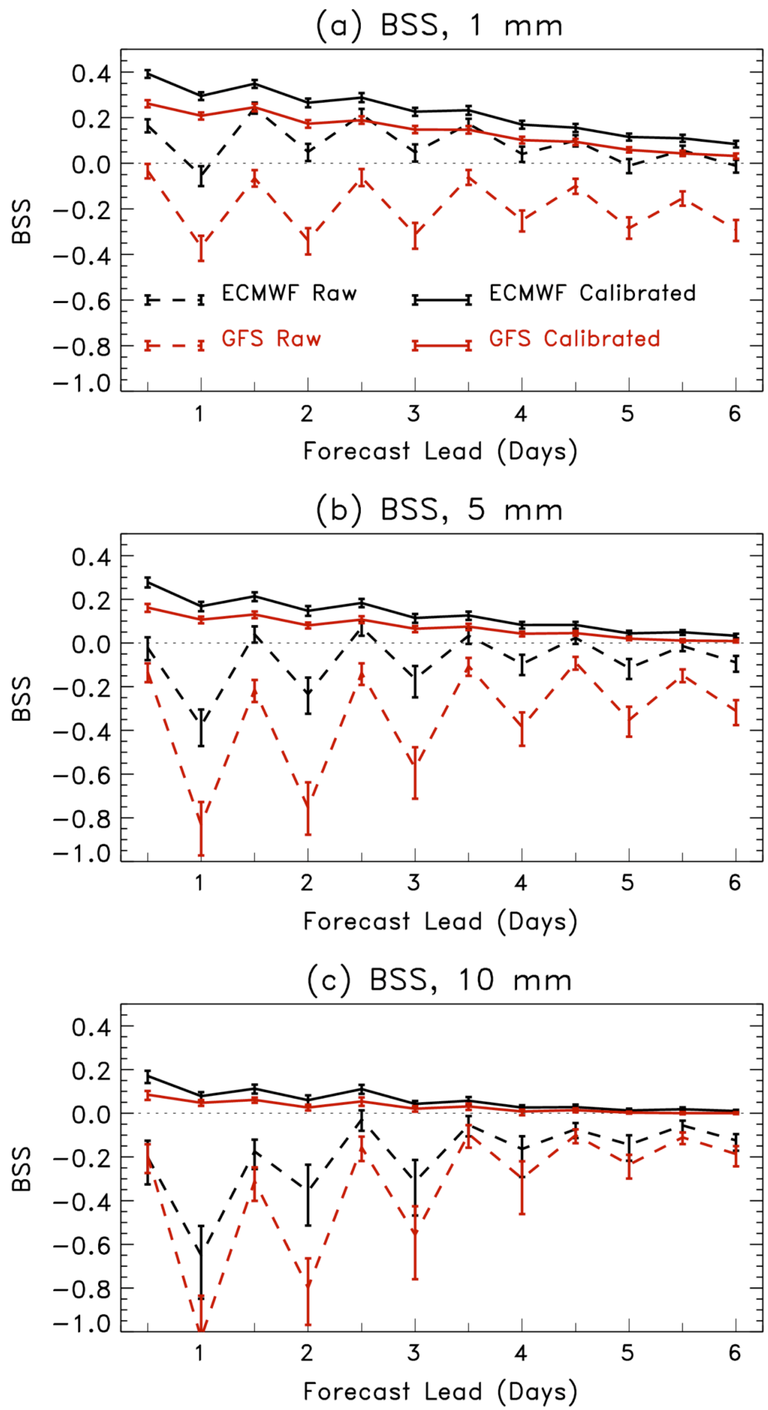
In some respects
GFS forecasts
look more calibrated
but the frequency
of usage histograms
show ECMWF sharper
and thus more skillful.



Brier Skill Scores

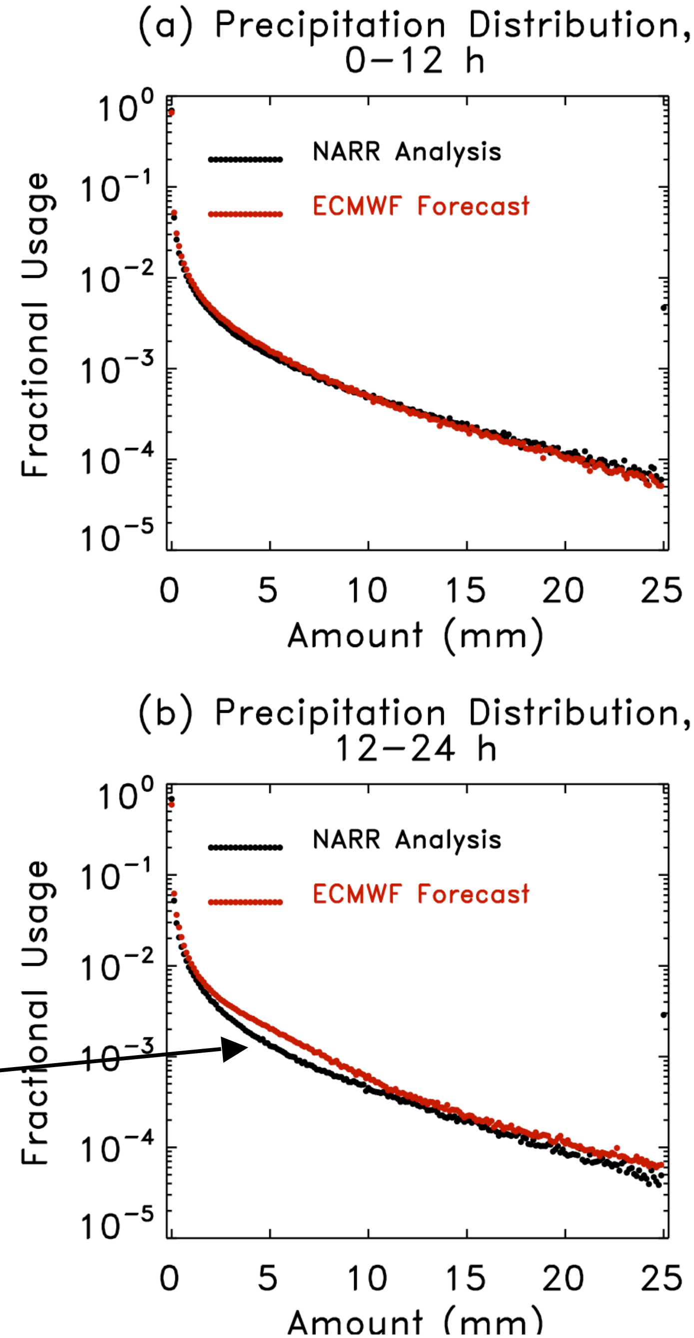
Notes:

(1) Diurnal oscillation in raw forecast skill
(2) Raw forecast skill poor, especially at higher thresholds
(3) Calibration has substantial positive impact.
(4) ECMWF > GFS skill.
(5) Multimodel not plotted, ~ same as ECMWF calibrated

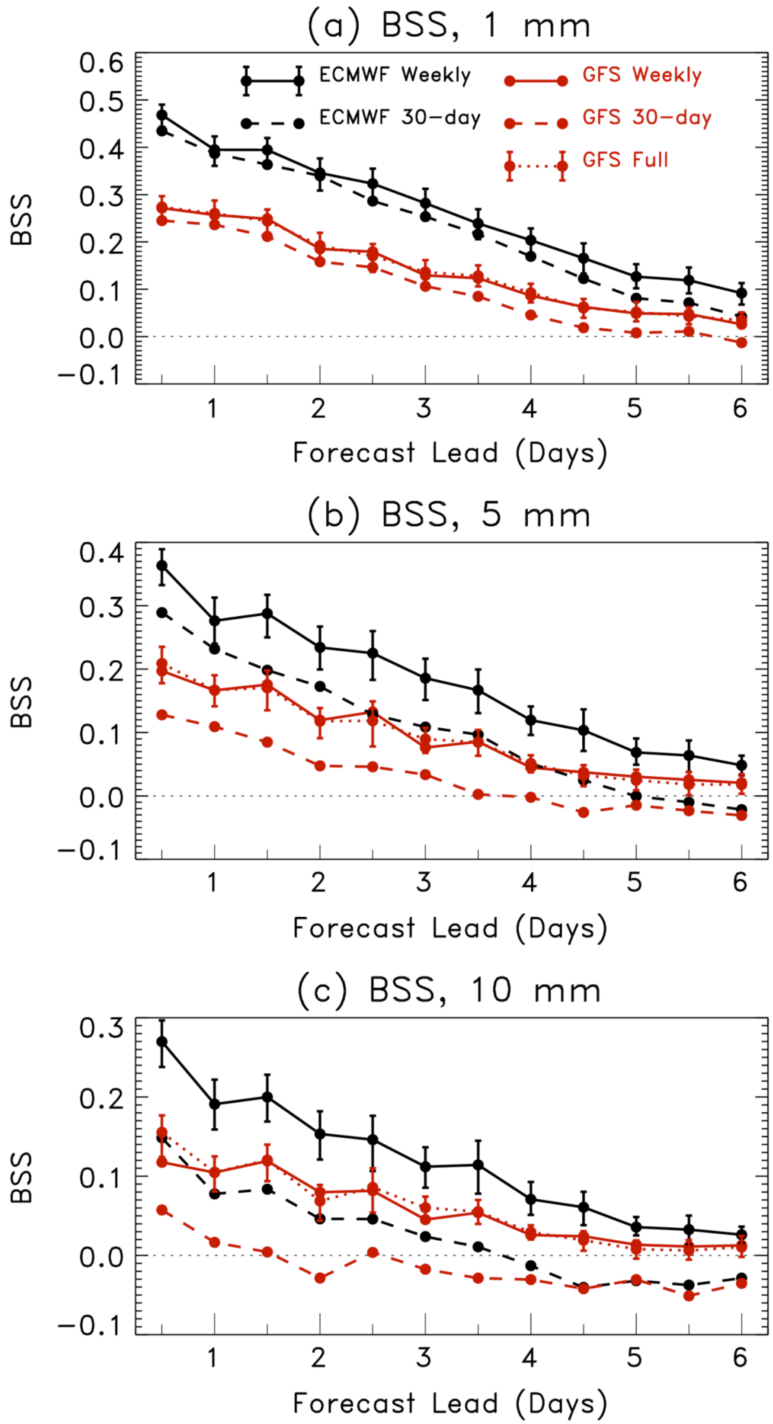


Why are 12Z - 00Z forecasts less skillful?

Over-forecast bias in models during daytime relative to NARR



Precipitation skill with weekly, 30-day, and full training data sets



Notes:

(1) Substantial benefit of weekly relative to 30-day training data sets, especially at high thresholds.

(2) Not much benefit from full relative to weekly reforecasts.

Conclusions

- Still a large benefit from forecast calibration, even with state-of-the-art ECMWF forecast model.
- Temperature calibration:
  - Short leads: a few previous forecasts adequate for calibration
  - Long leads: better skill with long reforecast training data set.
- Precipitation calibration
  - Low thresholds: a few previous forecasts somewhat ok for calibration
  - Larger thresholds: large benefit from large training data set.
  - Skill when trained with daily data not much larger than when trained with weekly data (preliminary result, more testing needed).

Other research issues

- Optimal reforecast ensemble size?
  – Other results suggest ~ 5 members
- Optimal frequency, length of reforecasts data sets?
  – Multi-decadal, but every day may not be necessary
- End-to-end linkages into hydrologic prediction systems.
- New applications (fire weather, severe storms, wind forecasting).

Are operational centers heading toward reforecasting?

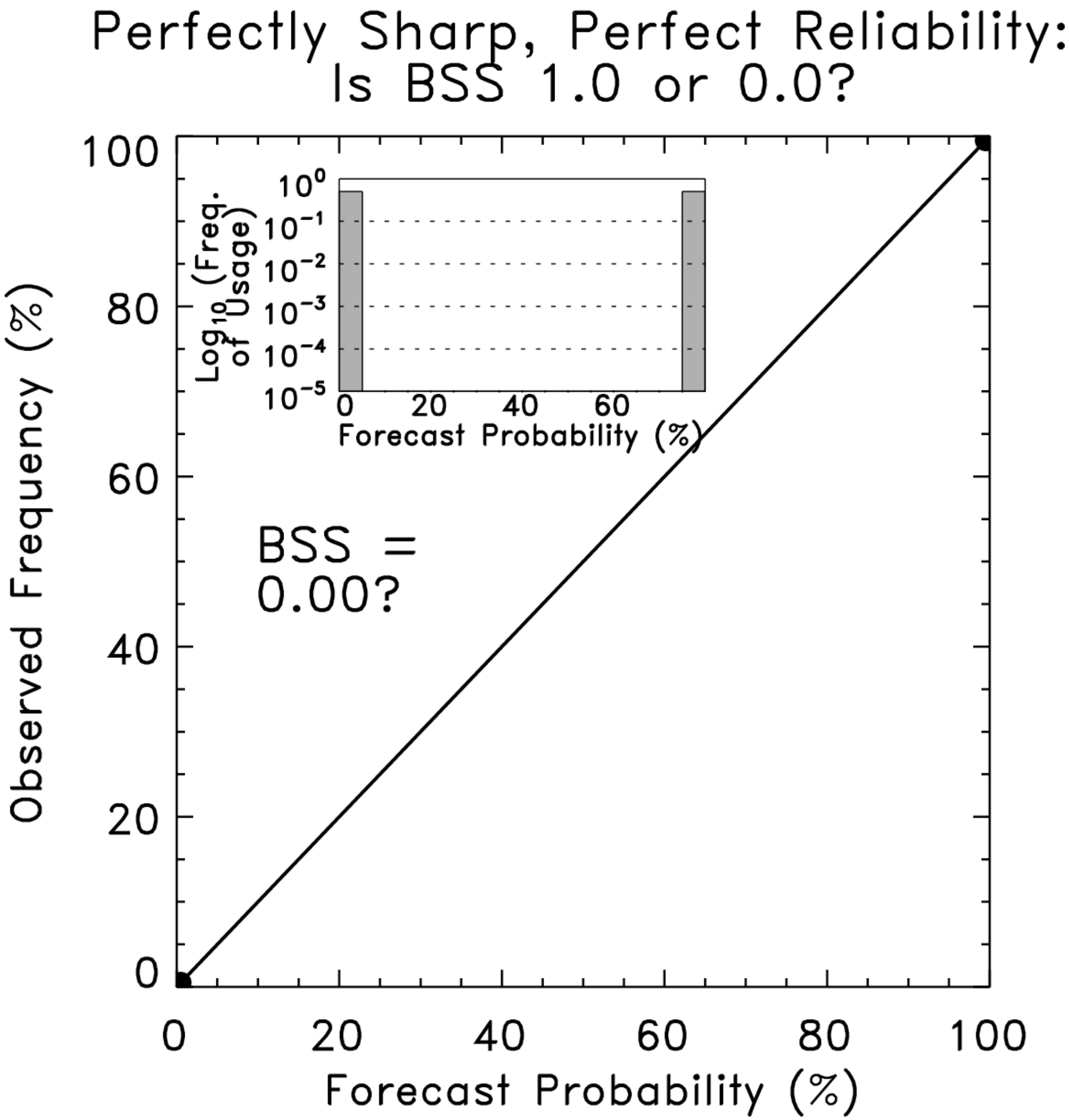
- **NCEP**: tentative plans for 1-member real-time reforecast.
- **ECMWF**: once-weekly, real-time 5-member reforecast starting early 2008.
- **RPN Canada**: planning ~5-year reforecast data set, delayed by budget and staffing issues.

References

- Hagedorn, R., T. M. Hamill, and J. S. Whitaker, 2007: Probabilistic forecast calibration using ECMWF and GFS ensemble forecasts. Part I: surface temperature. *Mon. Wea. Rev*., submitted. Available at http://tinyurl.com/3axuac

- Hamill, T. M., J. S. Whitaker, and R. Hagedorn, 2007: Probabilistic forecast calibration using ECMWF and GFS ensemble forecasts. Part II: precipitation. *Mon. Wea. Rev*., submitted. Available at http://tinyurl.com/38jgkv

- (and references therein)



This is normally considered the reliability diagram of a perfect forecast. But suppose half the samples are from a location where the forecast probability is always zero, and the other half from a location where the forecast probability is always 1.0. Then even if the forecast is correct in both locations, it's never better than climatology… so skill should = 0.0 !

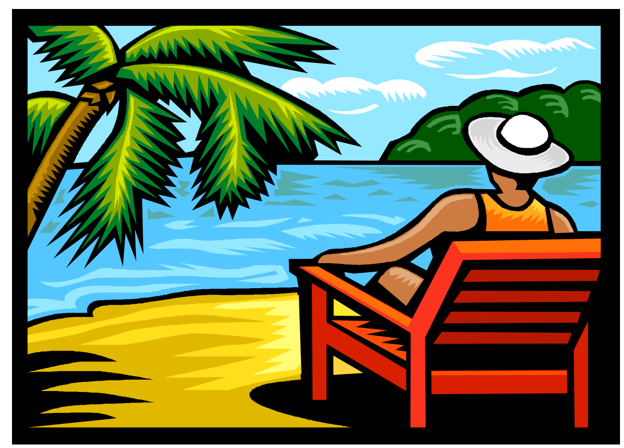
A thought experiment: two islands

Each island's forecast is an ensemble formed from a random draw from its climatology, ~ N($\pm\ \alpha$,1)

Island 2: ~N($-\alpha$,1)

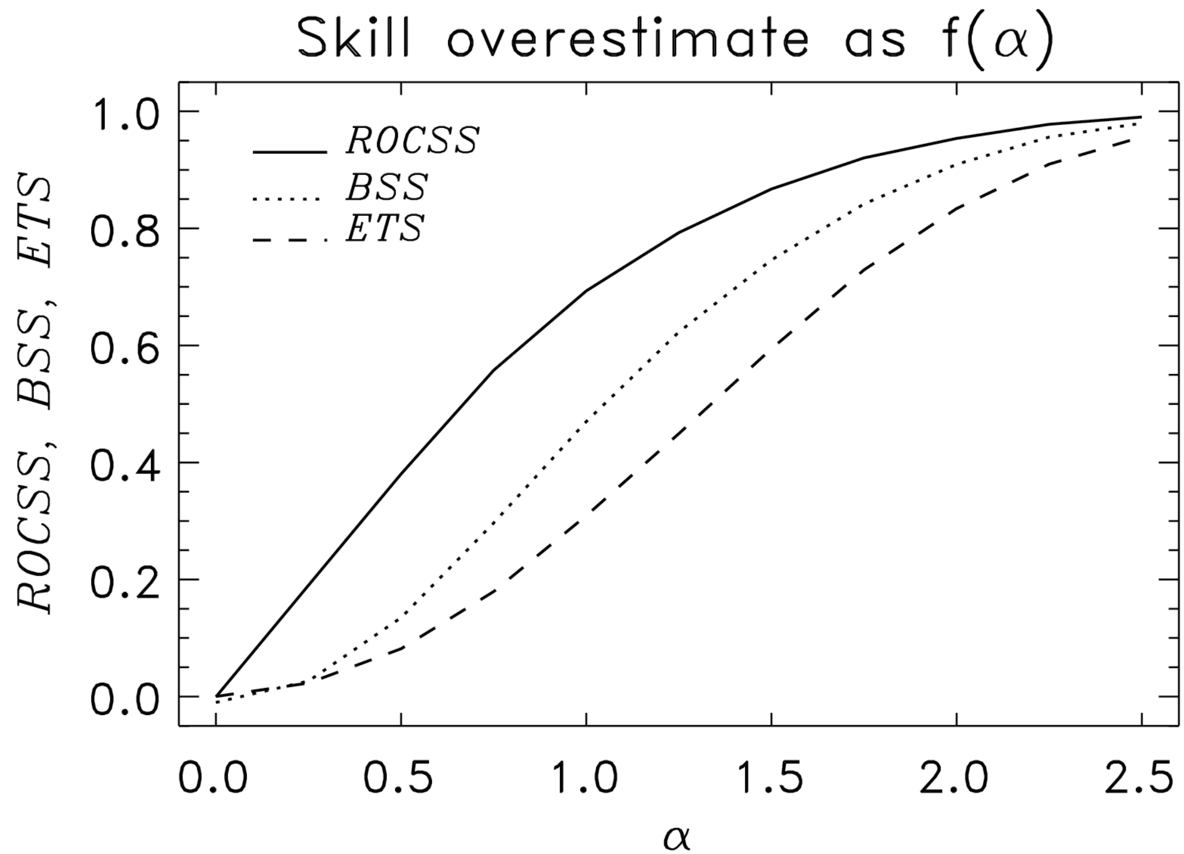
← As α increases… →

Island 1: ~N(α,1)



Expect no skill relative to climatology for the event P(Obs) > 0.0 for common meteorological verification methods like Brier Skill Score, Equitable Threat Score, ROC skill score.

Skill with conventional methods of calculation



Reference climatology implicitly becomes
$N(+\alpha,1)$ + $N(-\alpha,1)$ not $N(+\alpha,1)$ OR $N(-\alpha,1)$

Statisticians hinted at this long ago…

"*One method that is sometimes used is to combine all the data into a single 2x2 table….this procedure is legitimate only if the probability **p** of an occurrence (on the null hypothesis) can be assumed to be the same in all the individual 2x2 tables. Consequently, if **p** obviously varies from table to table, or we suspect that it may vary, this procedure should not be used.*"

W.G. Cochran, 1954, from "Some methods of strengthening common χ^2 tests" (*Biometrics*)