

# **Review of UWME Forecast Performance and Post-Processing**

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# Multi-Analysis Collection

Abbreviation/Model/Source	Type	Resolution (~ @ 45 °N)		Objective Analysis
		Computational	Distributed	
 <b>gfs</b> , Global Forecast System (GFS), National Centers for Environmental Prediction	Spectral	T254 / L64 ~55 km	1.0° / L14 ~80 km	SSI 3D Var
 <b>cmcg</b> , Global Environmental Multi-scale (GEM), Canadian Meteorological Centre	Finite Diff	0.9°×0.9°/L28 ~70 km	1.25° / L11 ~100 km	3D Var
 <b>eta</b> , limited-area mesoscale model, National Centers for Environmental Prediction	Finite Diff.	12 km / L45	90 km / L37	SSI 3D Var
 <b>gasp</b> , Global Analysis and Prediction model, Australian Bureau of Meteorology	Spectral	T239 / L29 ~60 km	1.0° / L11 ~80 km	3D Var
 <b>jma</b> , Global Spectral Model (GSM), Japan Meteorological Agency	Spectral	T106 / L21 ~135 km	1.25° / L13 ~100 km	OI
 <b>ngps</b> , Navy Operational Global Atmos. Pred. System, Fleet Numerical Meteorological & Oceanographic Cntr.	Spectral	T239 / L30 ~60 km	1.0° / L14 ~80 km	OI
 <b>tcwb</b> , Global Forecast System, Taiwan Central Weather Bureau	Spectral	T79 / L18 ~180 km	1.0° / L11 ~80 km	OI
 <b>ukmo</b> , Unified Model, United Kingdom Meteorological Office	Finite Diff.	5/6°×5/9°/L30 ~60 km	<i>same</i> / L12	3D Var

# Old UWME and UWME+ Physics Configuration

(October 2002 – January 2005)

IC	ID#	PBL			Cloud Microphysics	Cumulus			Radiation	SST Perturbation	Land Use Table
			Soil	vertical diffusion		36-km Domain	12-km Domain	shlw. cumls.			
UWME		MRF	5-Layer	Y	Simple Ice	Kain-Fritsch	Kain-Fritsch	N	cloud	<i>standard</i>	<i>standard</i>
UWME+											
avn	plus01	MRF	LSM	Y	Simple Ice	Kain-Fritsch	Kain-Fritsch	Y	RRTM	SST_pert01	LANDUSE.plus1
cmcg	plus02	MRF	5-Layer	Y	Reisner II	Grell	Grell	N	cloud	SST_pert02	LANDUSE.plus2
eta	plus03	Eta	5-Layer	N	Goddard	Betts-Miller	Grell	Y	RRTM	SST_pert03	LANDUSE.plus3
gasp	plus04	MRF	LSM	Y	Shultz	Betts-Miller	Kain-Fritsch	N	RRTM	SST_pert04	LANDUSE.plus4
jma	plus05	Eta	LSM	N	Reisner II	Kain-Fritsch	Kain-Fritsch	Y	cloud	SST_pert05	LANDUSE.plus5
ngps	plus06	Blackadar	5-Layer	Y	Shultz	Grell	Grell	N	RRTM	SST_pert06	LANDUSE.plus6
tcwb	plus07	Blackadar	5-Layer	Y	Goddard	Betts-Miller	Grell	Y	cloud	SST_pert07	LANDUSE.plus7
ukmo	plus08	Eta	LSM	N	Reisner I	Kain-Fritsch	Kain-Fritsch	N	cloud	SST_pert08	LANDUSE.plus8

- Assumed differences between **model physics options** approximate model error coming from sub-grid scales

- Perturbed **surface boundary parameters** according to their suspected uncertainty

- Albedo
- Roughness Length
- Moisture Availability

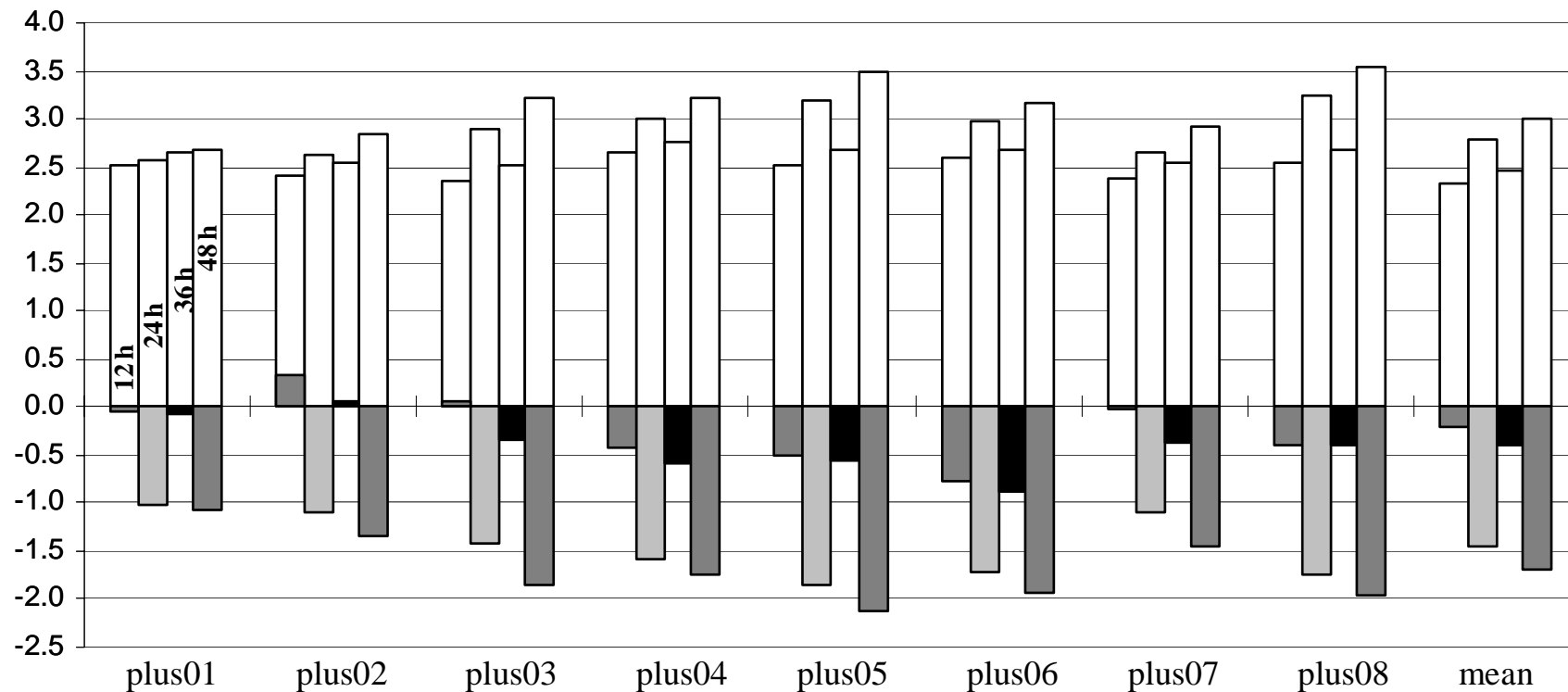
# Member-Wise Forecast Bias Correction

## 2-m Temperature

Average RMSE (°C)

and

(shaded) Average Bias



(0000 UTC Cycle; October 2002 – March 2003)

Eckel and Mass 2005

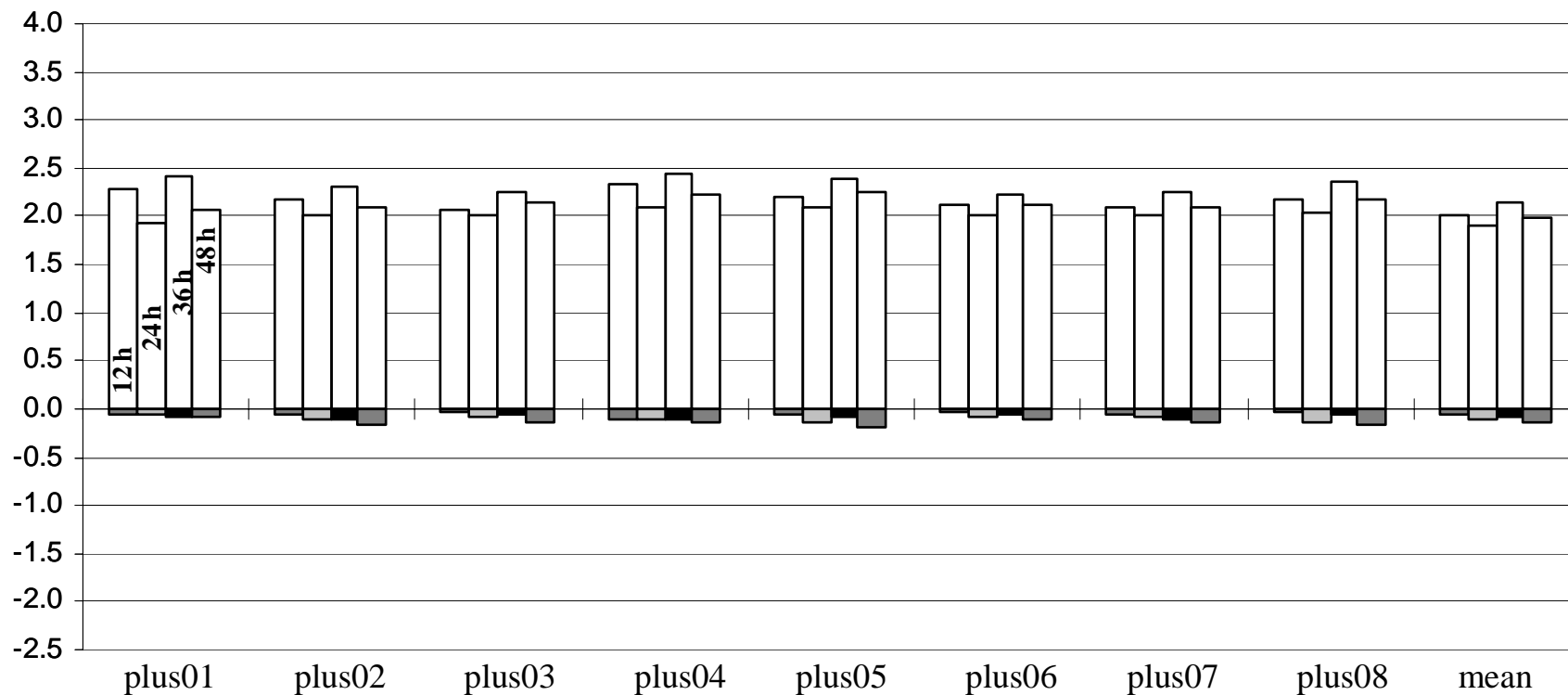
# Member-Wise Forecast Bias Correction

## 2-m Temperature 14-day additive bias correction

Average *RMSE* (°C)

and

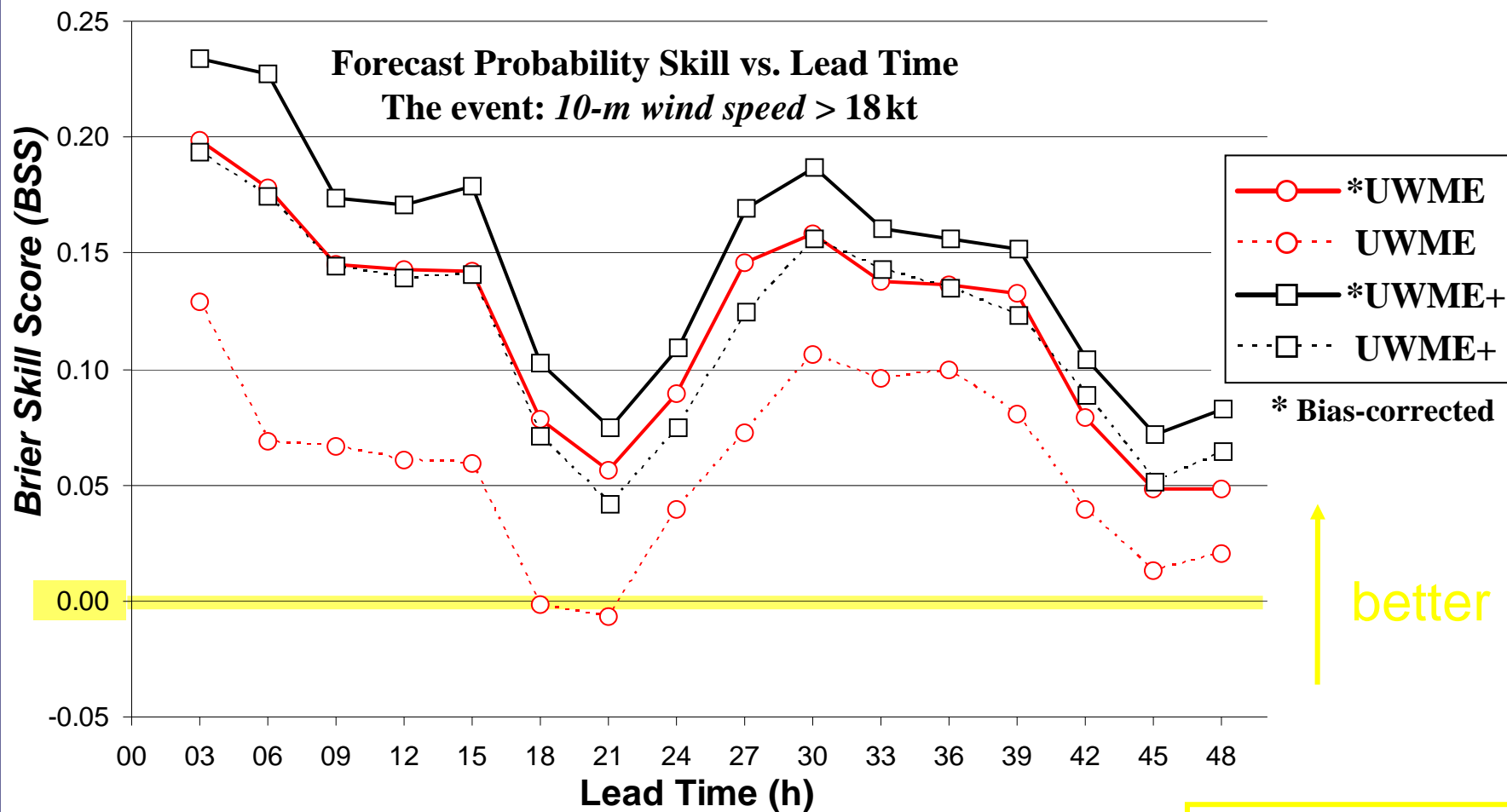
(shaded) Average Bias



(0000 UTC Cycle; October 2002 – March 2003)

Eckel and Mass 2005

# Forecast Probability Skill Example



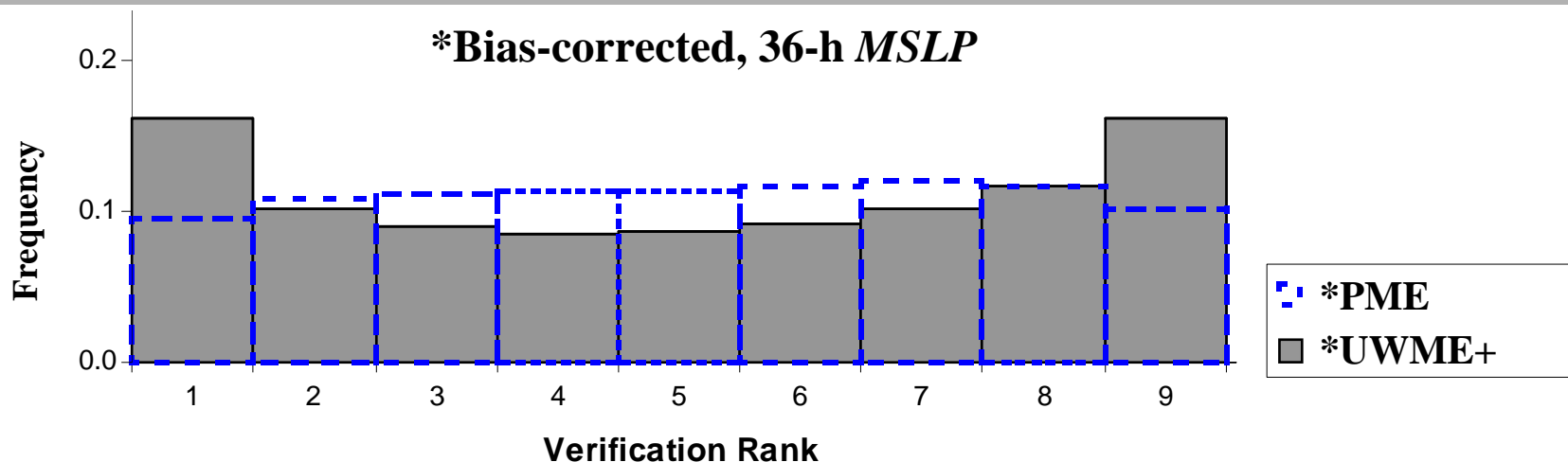
(0000 UTC Cycle; October 2002 – March 2003)

Eckel and Mass 2005

*BSS* = 1, perfect

*BSS* < 0, worthless

# Under-Dispersion Example



(0000 UTC Cycle; October 2002 – March 2003)

Eckel and Mass 2005

➤ **Poor Man's Ensemble (PME) exhibits more dispersion than \*UWME+**

- \*PME (a multi-model system) has more model diversity
- \*PME is better at capturing growth of synoptic-scale errors

“Nudging”  
MM5 outer  
domain may  
improve  
dispersion

## Verification Rank Histogram

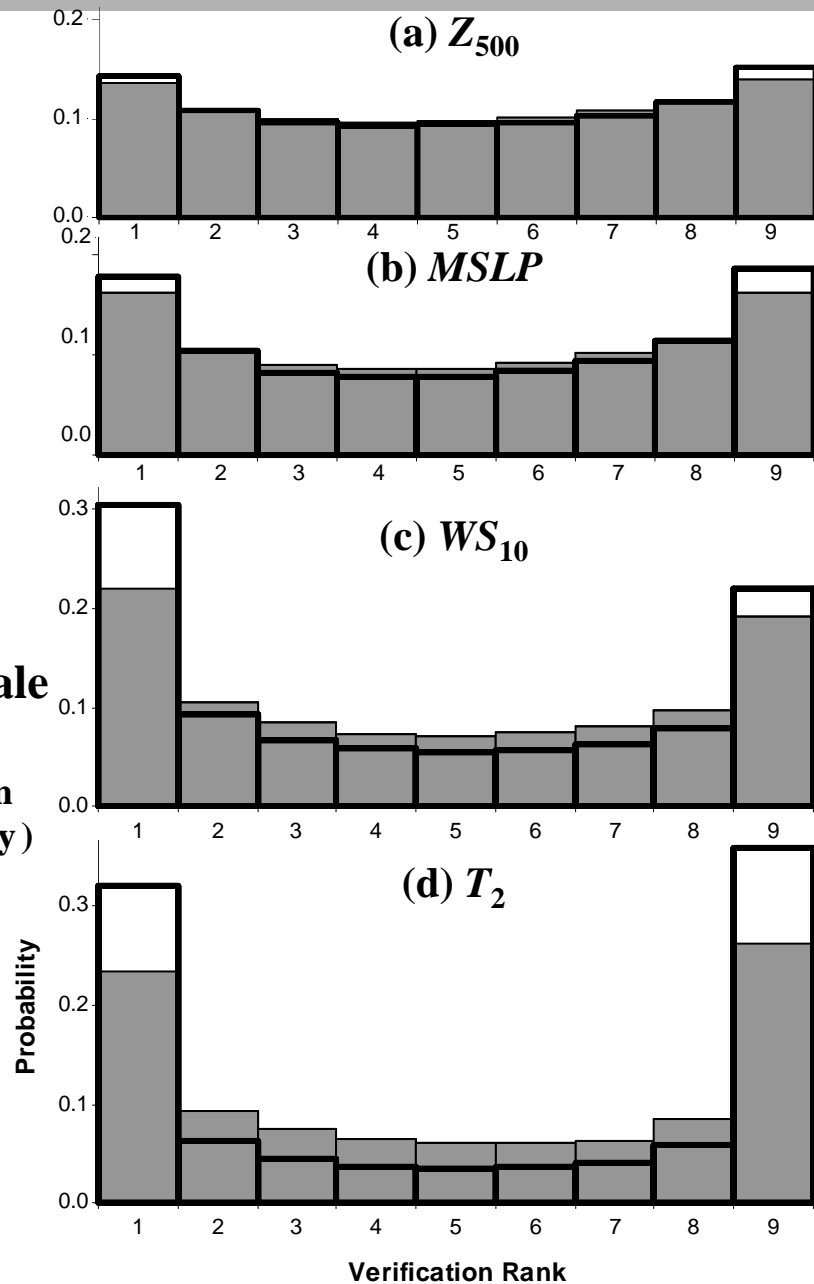
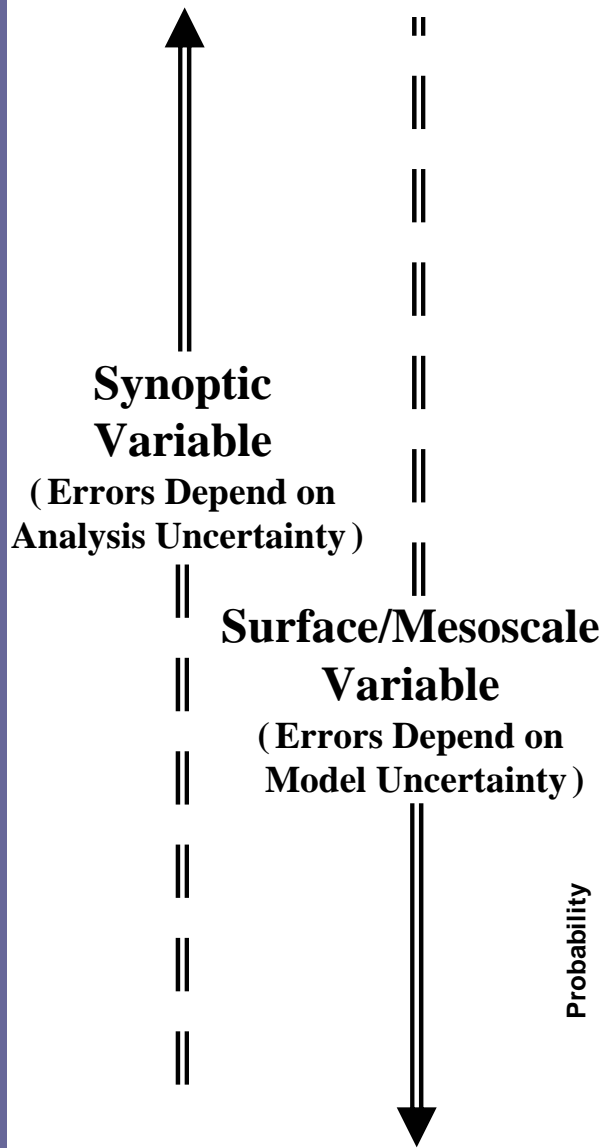
Record of where verification fell (i.e., its rank) among the ordered ensemble members:

Flat  **Well-calibrated** (truth is indistinguishable from ensemble members)

U-shaped  **Under-dispersive** (truth falls outside the ensemble range too often)

Humped  **Over-dispersive**

# Under-Dispersion by Variable



	<i>VOP</i>
*UWME	5.0%
*UWME+	4.2%
*UWME	9.0%
*UWME+	6.7%
*UWME	25.6%
*UWME+	13.3%
*UWME	43.7%
*UWME+	21.0%

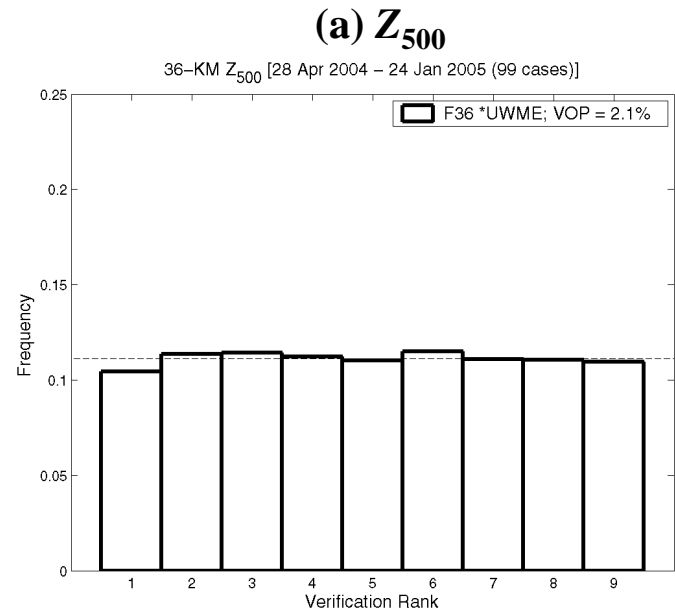


# Effect of Nudging

- FDDA (“nudging”) was applied to the 36-km domain on all UWME forecasts beginning 27 April 2004 with the 1200 UTC run.

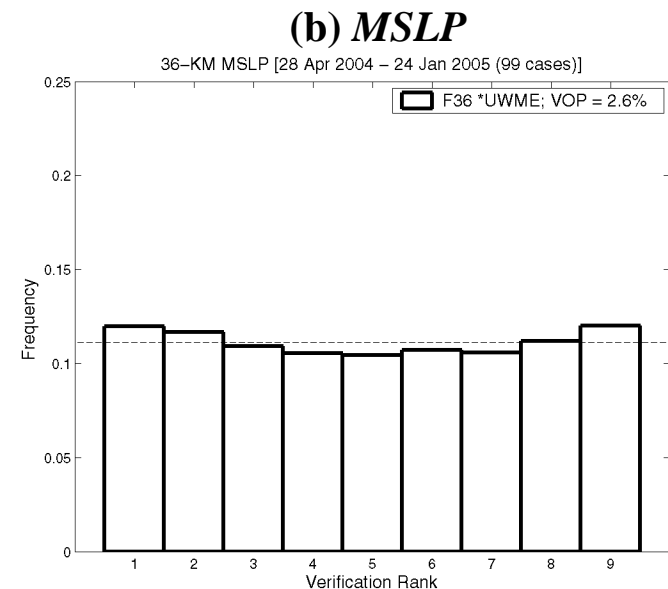
Has this helped?

- Apparently, the answer is **YES** for synoptic variables.
  - Although, there is some evidence for **over-dispersion** now ( $T_{850}$ , not shown).
  - Note that, comparisons with the non-nudged UWME are *not completely fair* due to different time periods of study.



VOP

2.1%



2.6%

(0000 UTC Cycle; April 2004 – January 2005)

## Post-Processing: Forecast Bias Correction

- Under-dispersion is NOT corrected.
  
- In fact, because this bias correction is applied to each member individually:
  - The ensemble spread is reduced.
  - The ensemble spread-skill relationship is degraded.  
(please visit my [poster](#) for more information on this topic!)
  
- One alternative is to estimate forecast bias from the ensemble mean and apply it to all members.
  - This is the usual approach.
  - This would preserve ensemble spread, which appears to be valuable in an under-dispersive system, even if it is “bad spread”.
  - The original spread-skill relationship, if one exists, would be maintained.
  - Probability forecast skill might be lower.

# Post-Processing: Probability Densities

Q: How should we infer forecast probability density functions from a finite ensemble of forecasts?

A: Some options are...

## ■ Democratic Voting (DV)

■  $P = x / M$

$x = \#$  members  $>$  or  $<$  threshold

$M = \#$  total members

## ■ Uniform Ranks (UR)<sup>\*\*\*</sup>

■ Assume flat rank histograms

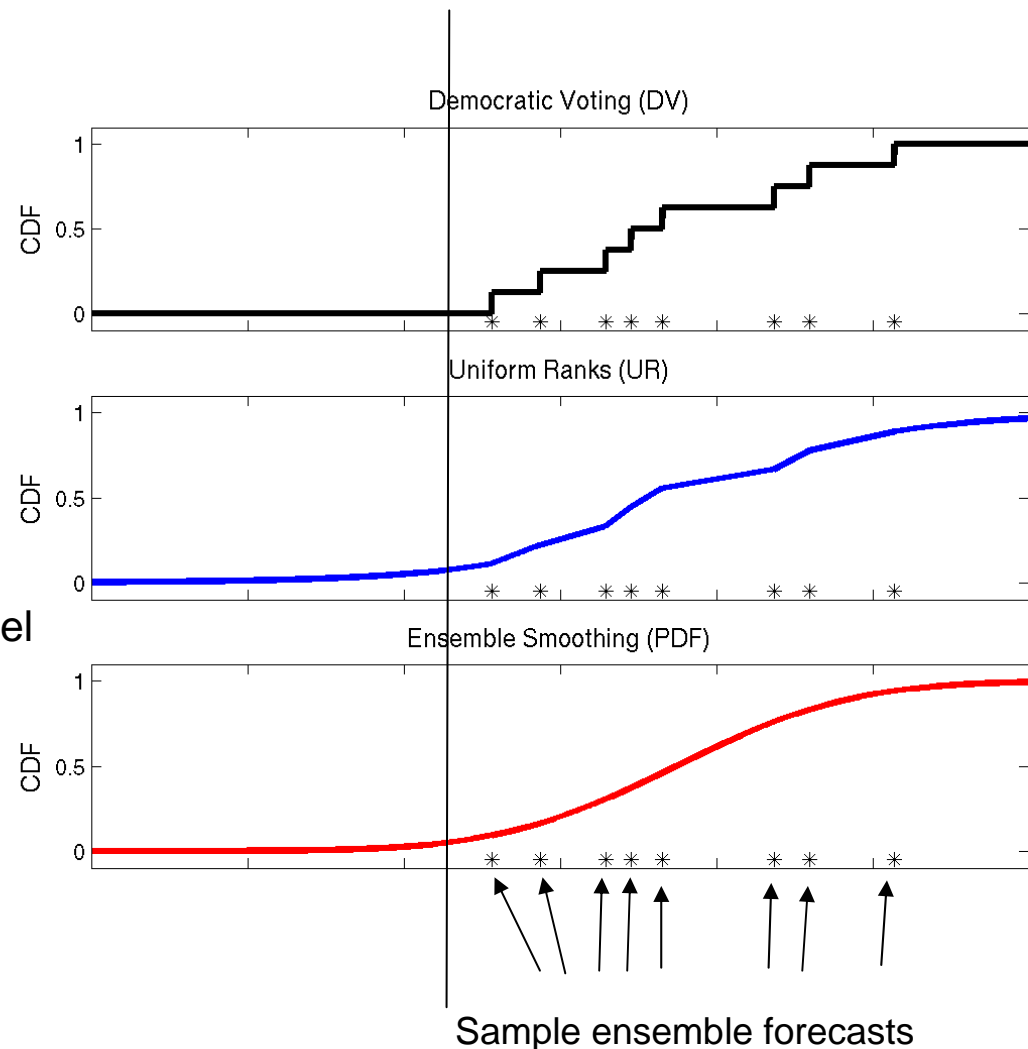
■ Linear interpolation of the DV probabilities between adjacent member forecasts

■ Extrapolation using a fitted Gumbel (extreme-value) distribution

## ■ Ensemble Smoothing (PDF)

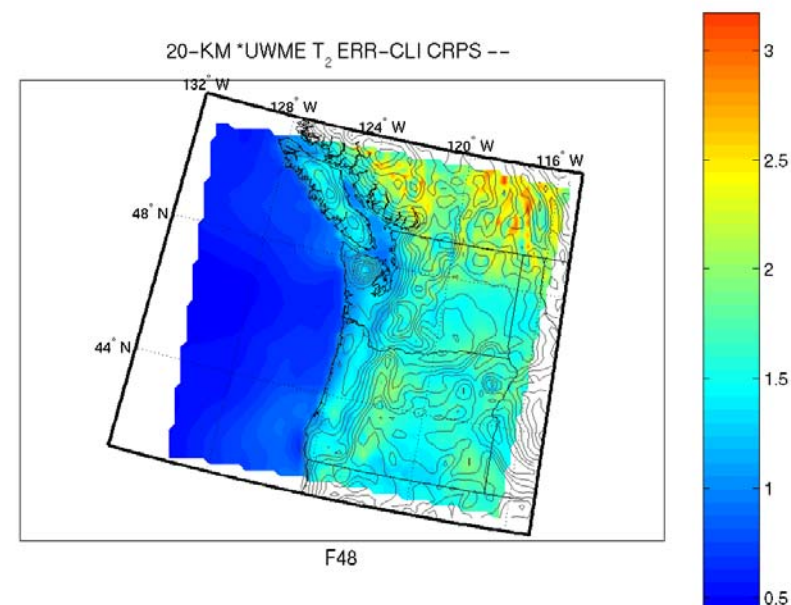
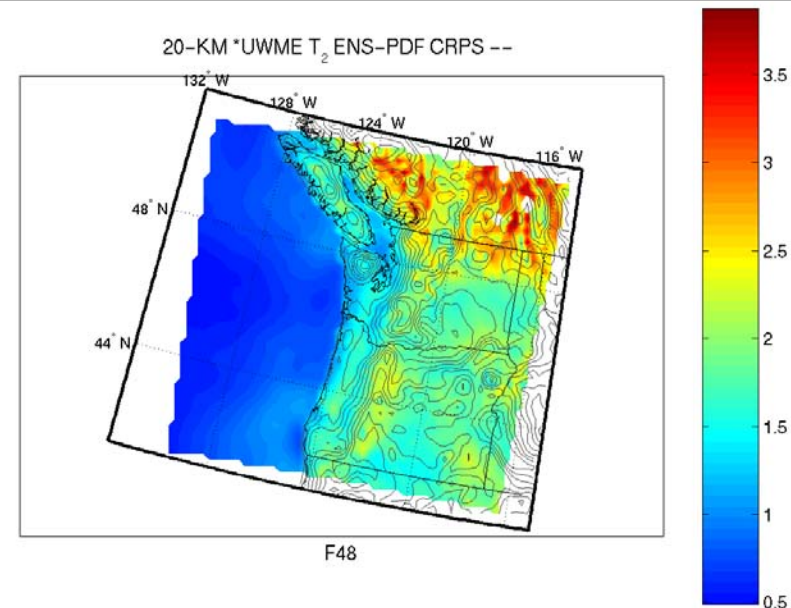
■ Fit a statistical distribution (e.g., normal) to the member forecasts

<sup>\*\*\*</sup>currently operational scheme



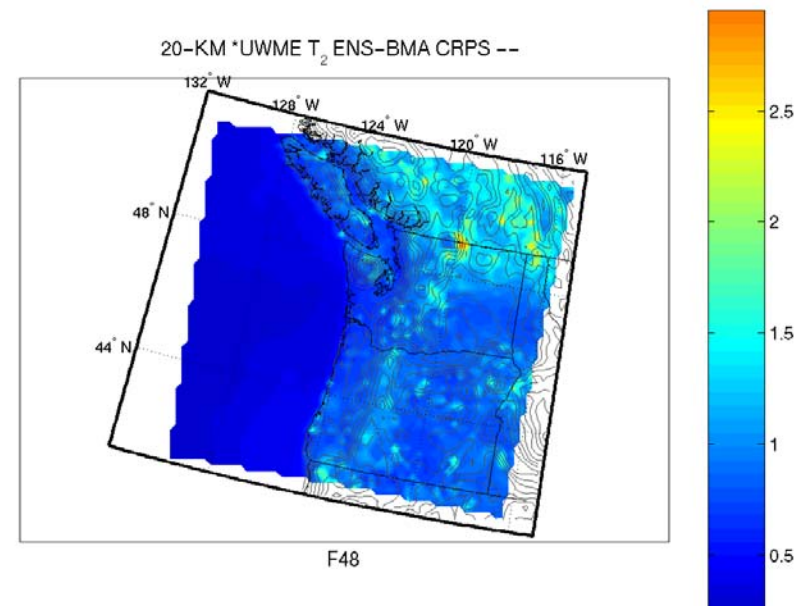
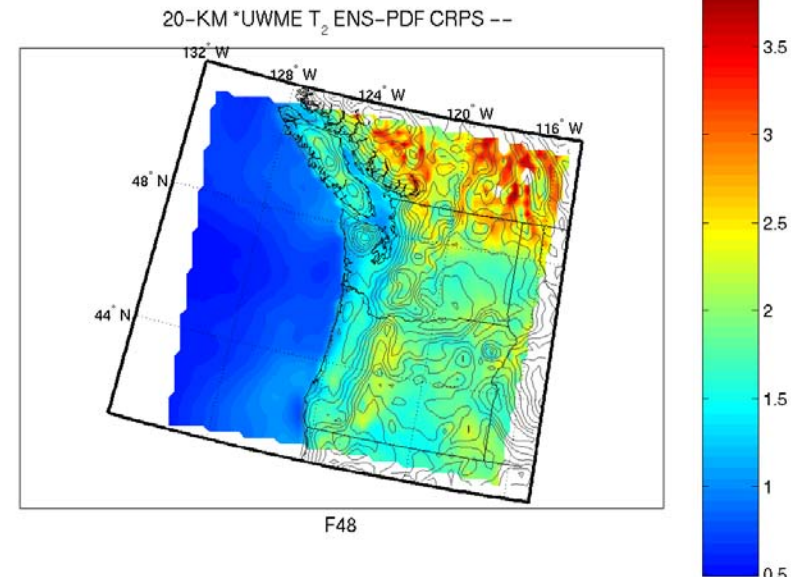
# Post-Processing: Calibration

- One can convert a deterministic forecast into a probabilistic forecast by “dressing” it with its historical forecast error statistics.
  - Such a probability forecast is time-invariant (a static forecast of uncertainty; a climatology).
  - Such a probability forecast is **calibrated** for large samples, **but not very sharp**.
- For the ensemble mean, we shall call this forecast mean error climatology (MEC).
- We have found that MEC performs extremely well (e.g., 48-h 2-m temperature forecasts at right).
  - MEC consistently outperforms the ensemble PDF.

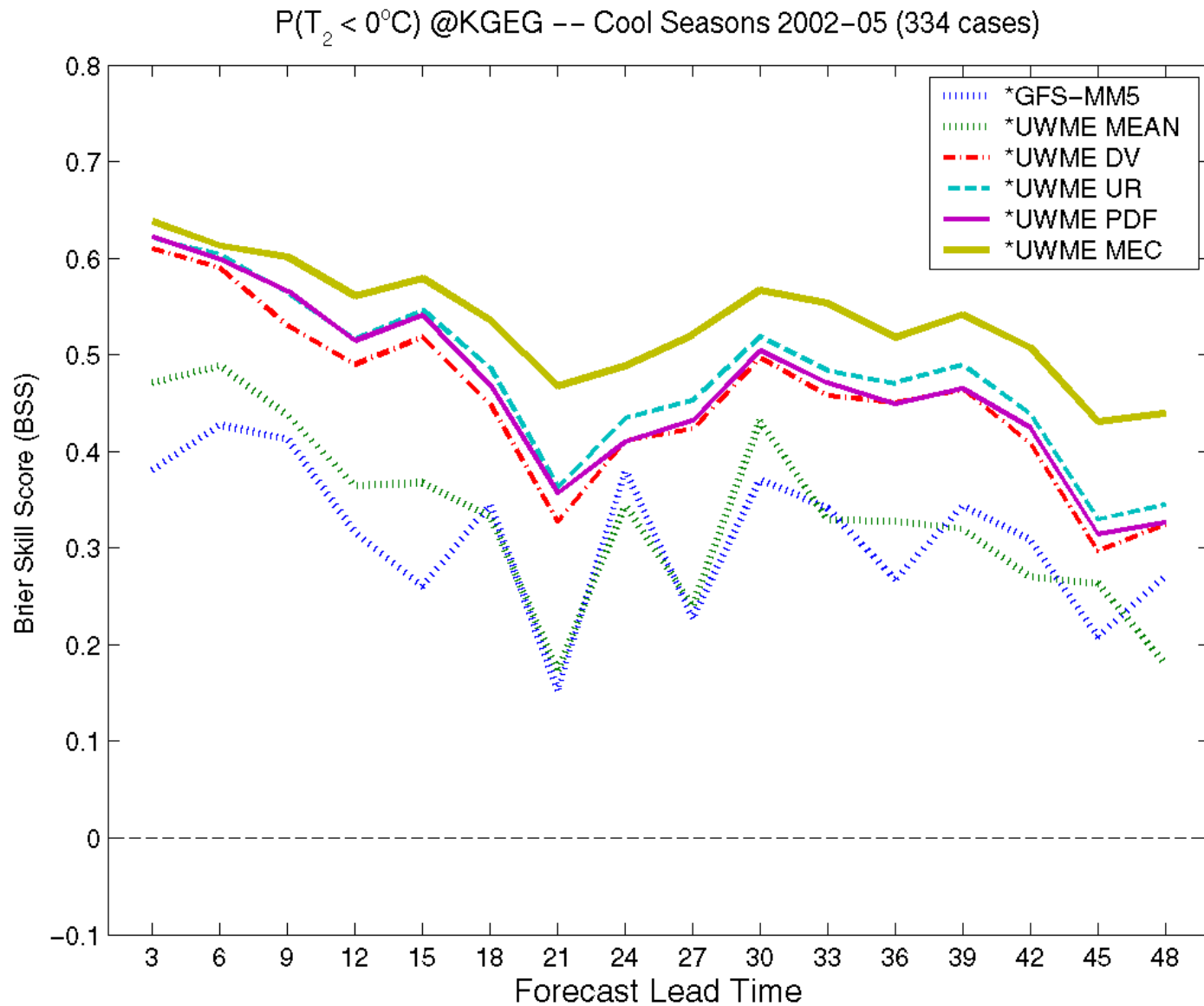


# Post-Processing: Calibration

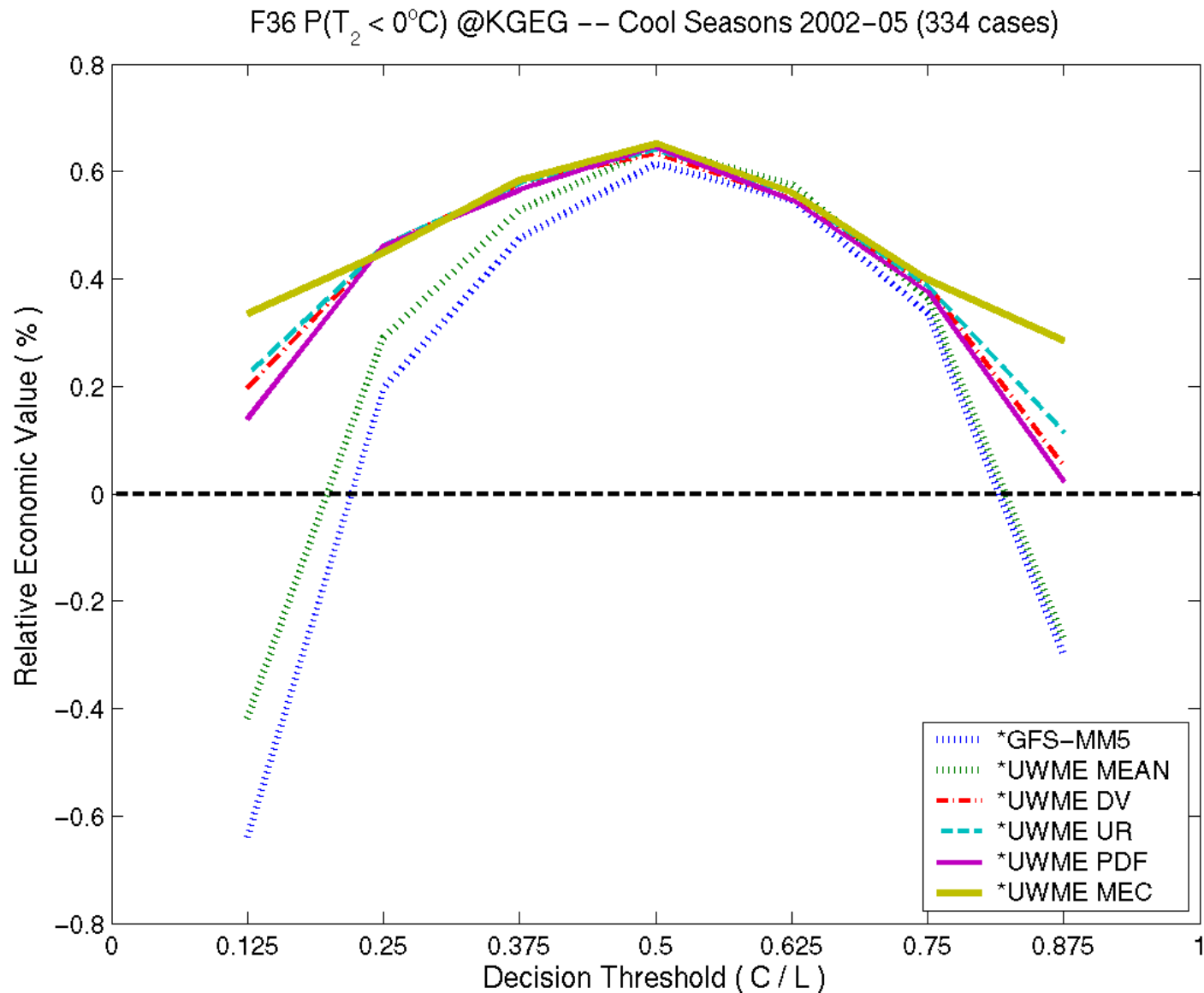
- Bayesian Model Averaging (BMA) has several advantages:
  - Time-varying uncertainty forecast
  - A way to keep multi-modality, if it is warranted
  - Can use short training periods with good results
- After several different attempts and configurations, we found that:
  - An adaptation of BMA where the training data is selected from a **neighborhood of grid points with similar land-use type and elevation** produced **EXCELLENT** results!
  - Example at right uses only 14 training days.



# A Concrete Example



# A Concrete Example



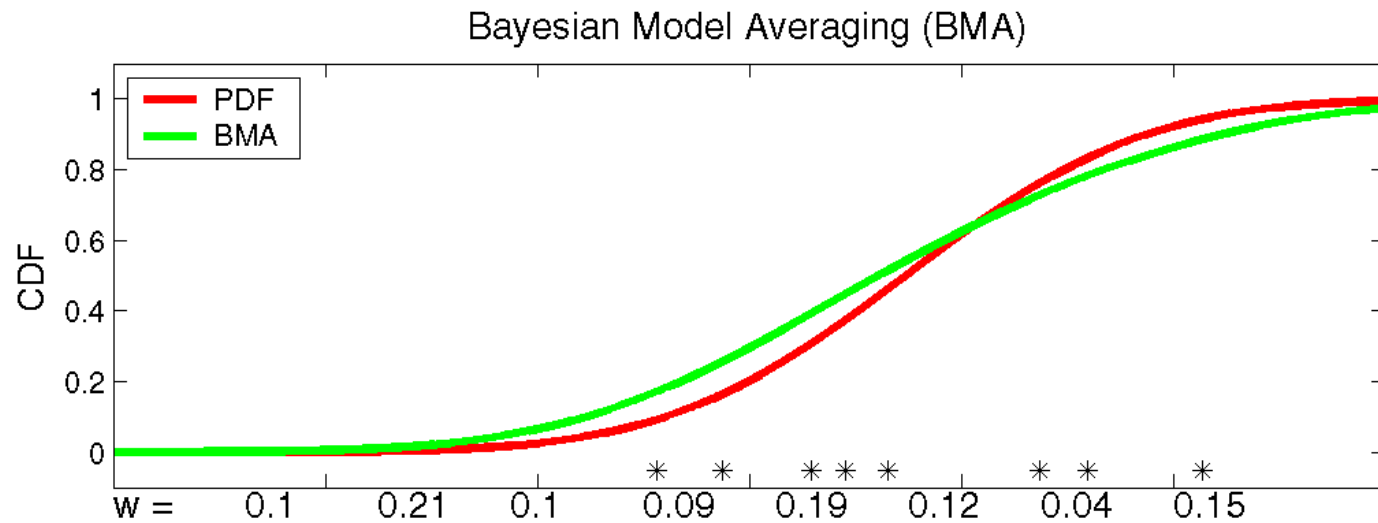
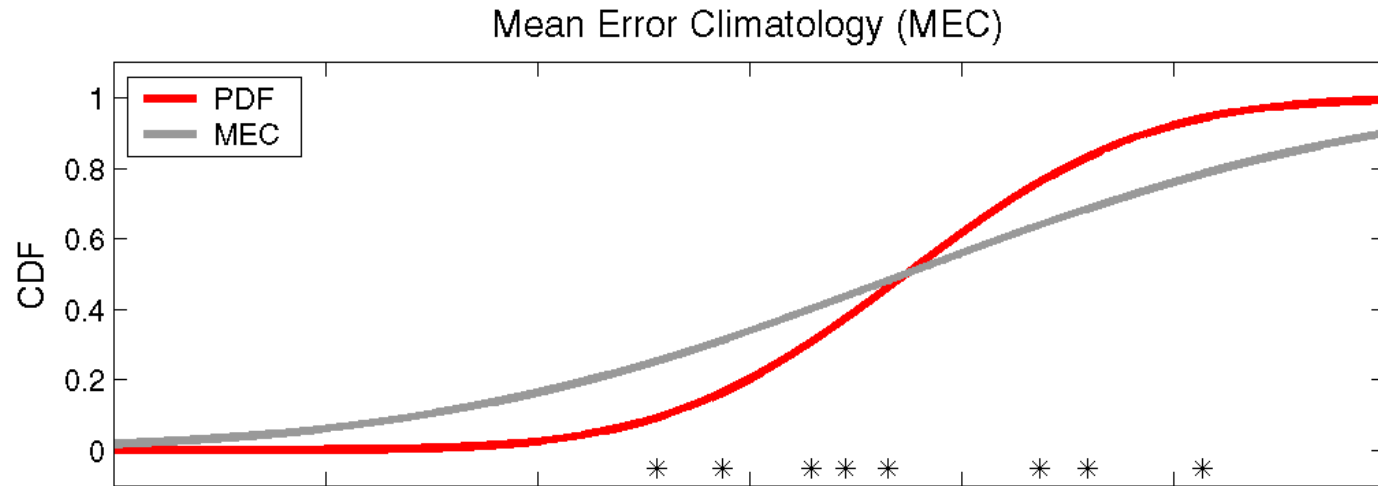
← **Minimize Misses**

**Minimize False Alarms** →

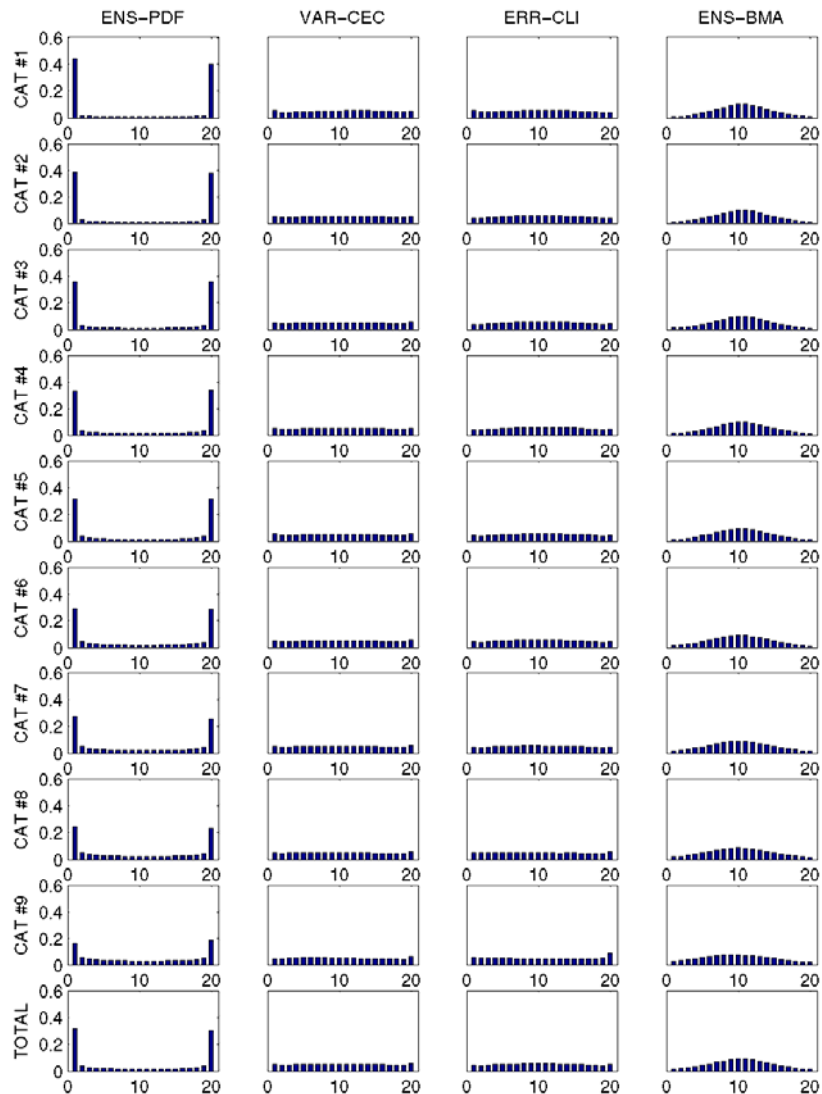
## **Extra Slides**



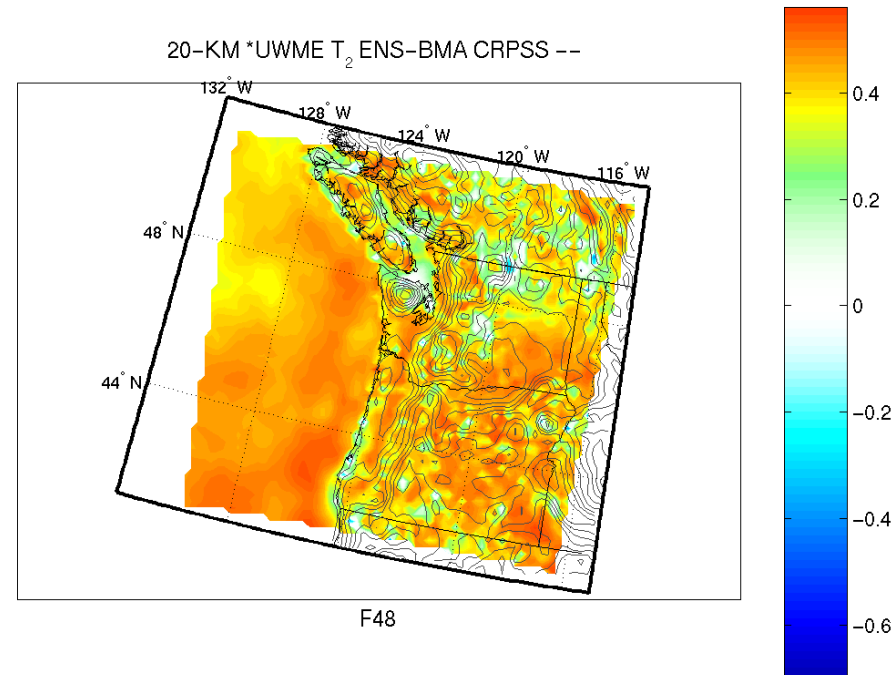
# Post-Processing: Probability Densities



# BMA – Neighbor\* Weights/Variance



## BMA improvement over MEC

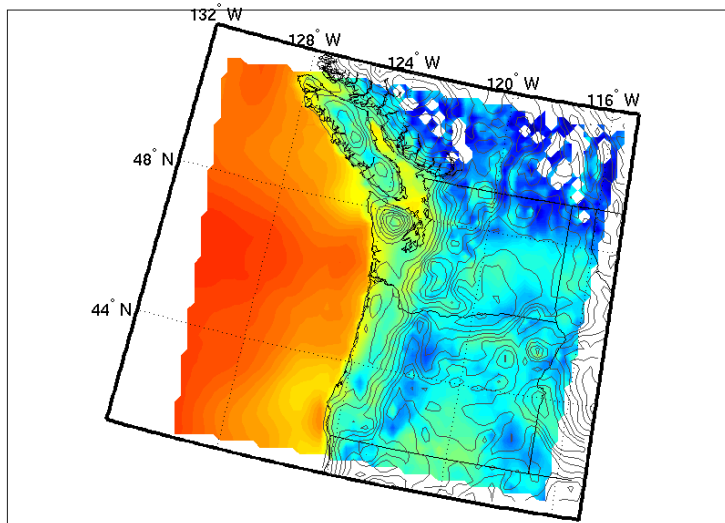


\*neighbors have same land use type and elevation difference < 200 m within a search radius of 3 grid points (60 km)

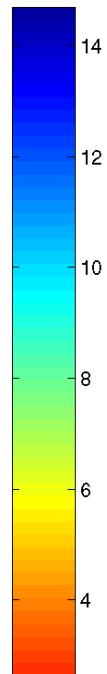
# 90% Prediction Interval Widths (Sharpness)

## ERR-CLI

20-KM \*UWME T<sub>2</sub> ERR-CLI 90% PI WIDTH --

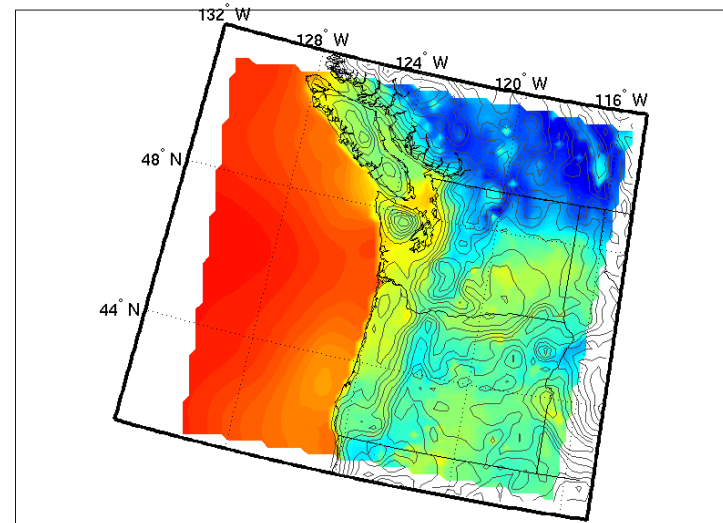


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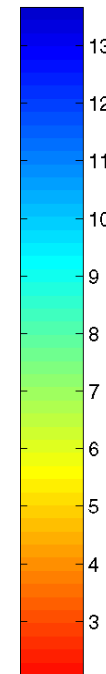


## BMA – Neighbor Weights/Variance

20-KM \*UWME T<sub>2</sub> ENS-BMA 90% PI WIDTH --



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## **Panel Discussion:**

**How do we effectively communicate probabilistic weather information to the public and users?**

# The “Academic” Perspective

- **#1: Know the limitations of the probabilistic forecasts you are communicating!**
  - Is it a “calibrated” probabilistic product? (can it be taken at face value?)
  - What is the size of the ensemble from which this product is generated? (what implications does that have for rare/extreme events?)
  - At what forecast lead time does this product cease to have value? (when should you switch to using a climatology-based product?)

- **#2: Know your users!**

- What is the relative cost of false alarms vs. missed events???



- **#3: Presentation, presentation, presentation!**
  - TV, internet, newspaper, radio



