FORECAST JUMPINESS: GOOD OR BAD?

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http://wwwt.emc.ncep.noaa.gov/gmb/ens/index.html

OUTLINE / SUMMARY

- **Definition of jumpiness**
  - Changes in forecast error
    - Magnitude
    - Pattern
- **Forecaster's desire**
  - Small error
  - Low jumpiness
- **NWP principles**
  - Jumpiness increases in single forecast as error variance is decreased
- **Solution**
  - Ensemble forecasting
    - Must be "jump-free"
- **Measure of jumpiness**
  - Time consistency histogram
    - After analysis rank (Talagrand) histogram

BACKGROUND

- **Definition** of forecast jumpiness
  - When successive forecasts for same verifying event (in time/space) look different =>
  - Error in successive forecasts are different
    - Either ***size or pattern of error***

- **NWP forecast error characteristics**
  - Originate from imperfect
    - Initial conditions
    - Numerical models
  - Amplify due to chaotic dynamics

- Some **model related errors** may be systematic
  - Stable from one initial condition to next
    - Not necessarily major source of forecast jumpiness?

- Successive **initial conditions** may have errors different in
  - Size or
  - ***Patterns*** – Focus of discussion

- **Jumpiness is not verification statistic**
  - Diagnostic of a DA/forecast system

- **Verification** metrics traditionally focus on **error variance** only
  - Not error pattern

JUMPINESS & USERS

- Objective of NWP development
  - Reduce forecast error variance
- Reduced error variance equals to
  - Reduced jumpiness in amplitude of errors
- Measure of forecast jumpiness at a given level of error variance
  - How correlated error patterns are in successive forecasts verifying at same time/space
- Preference of some/most/all (?) forecasters
  - NO JUMPINESS in error patterns
    - Users don't like big changes in forecasts
- Jumpiness is limitation of single value forecasts
  - Represent only one scenario
    - Do not convey forecast uncertainty
- Proper and only defendable format of forecasts
  - Probabilistic
    - Practical solution - Ensembles

JUMPINESS & NWP

- Is jumpiness a good or bad diagnostic feature for NWP systems?

- Good observing and analysis system
  - Error in analysis should be uncorrelated to error in background forecast =>
    - High jumpiness is necessary condition for good observing/DA systems
      - Not sufficient as low error variance is also a necessary condition

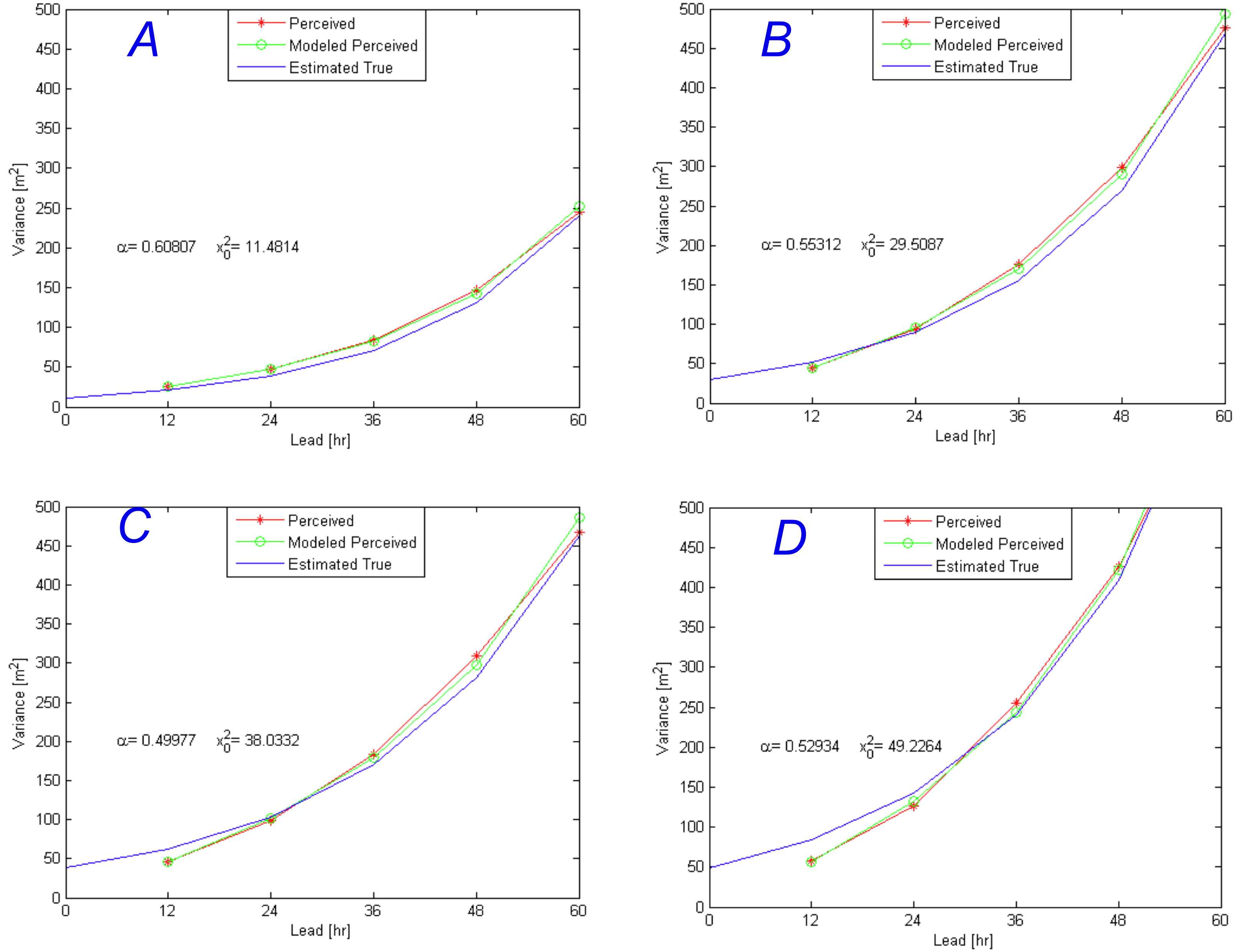
- Forecasters' desire for low jumpiness contradicts NWP principles
  - Lowering error variance necessarily leads to increased jumpiness

- Goal is to increase jumpiness, that's an artifact of decreasing error variance
  - Removing temporally correlated errors from DA/forecast system

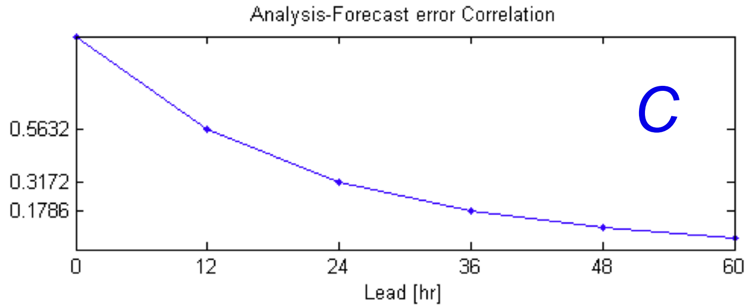
EXAMPLE OF GLOBAL NWP FORECASTS

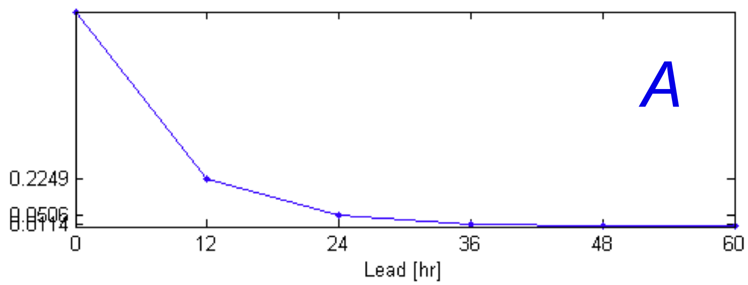
FORECAST ERROR VARIANCE

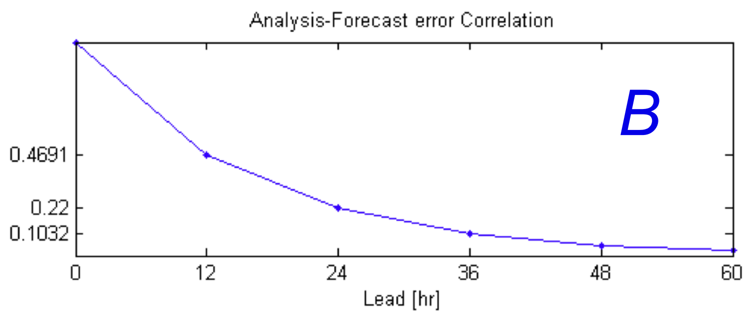
Pena & Toth

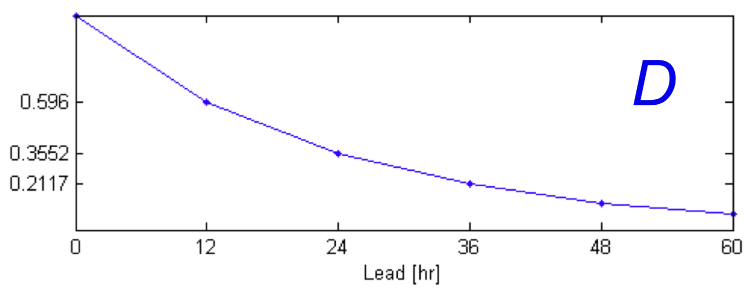


CORRELATION BETWEEN ANALYSIS & FORECAST ERRORS









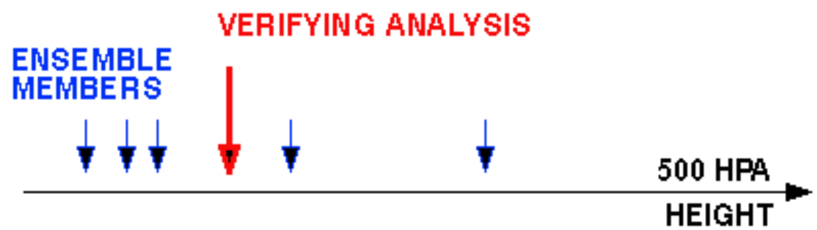
Pena & Toth

JUMPINESS & ENSEMBLE FORECASTS

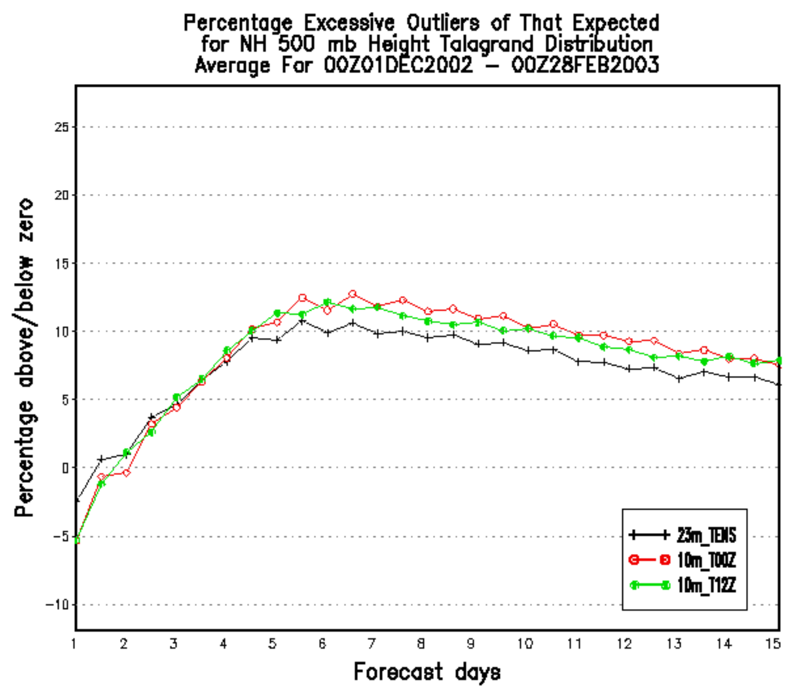
- Jumpiness is a virtue of single (control) NWP forecasts
  - Is it true for ensembles?
- Ensembles designed to capture forecast uncertainty
  - Successive ensembles must convey reduced uncertainty
    - Shorter range ensemble cloud must statistically lay within longer range cloud
- How to measure if an ensemble performs as it should?
- Method related to how we assess statistical consistency between ensemble and verifying analysis
  - Analysis Rank (or Talagrand) Histogram
- Measure temporal consistency in successive ensembles
  - Time consistency histogram
    - *Toth, Z., O. Talagrand, G. Candille, and Y. Zhu, 2002: Probability and ensemble forecasts (final draft). In: Environmental Forecast Verification: A practitioner's guide in atmospheric science. Ed.: I. T. Jolliffe and D. B. Stephenson. Wiley, pp. 137-164.*
- Role of analysis taken by members in succeeding ensemble

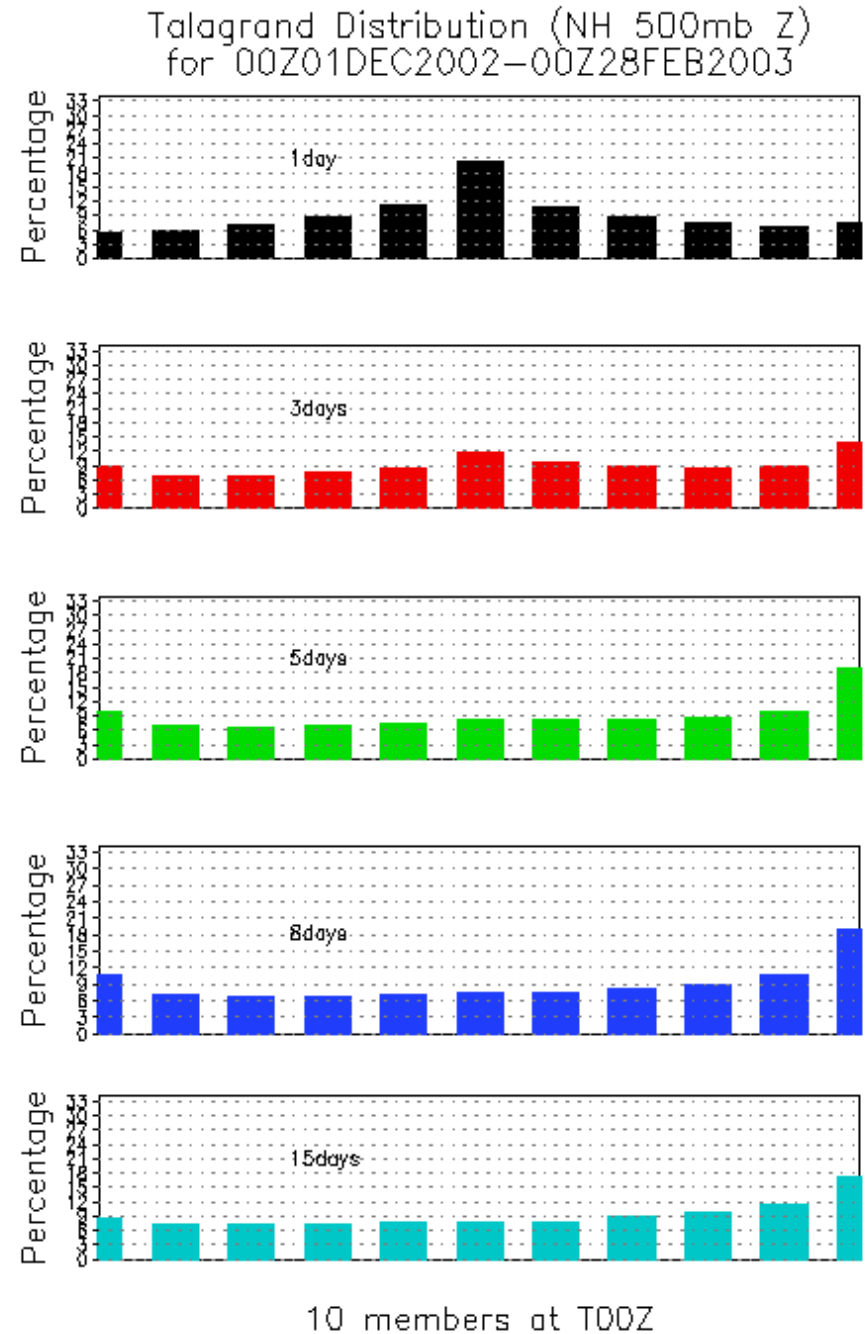
ANALYSIS RANK HISTOGRAM (TALAGRAND DIAGRAM)

MEASURE OF RELIABILITY

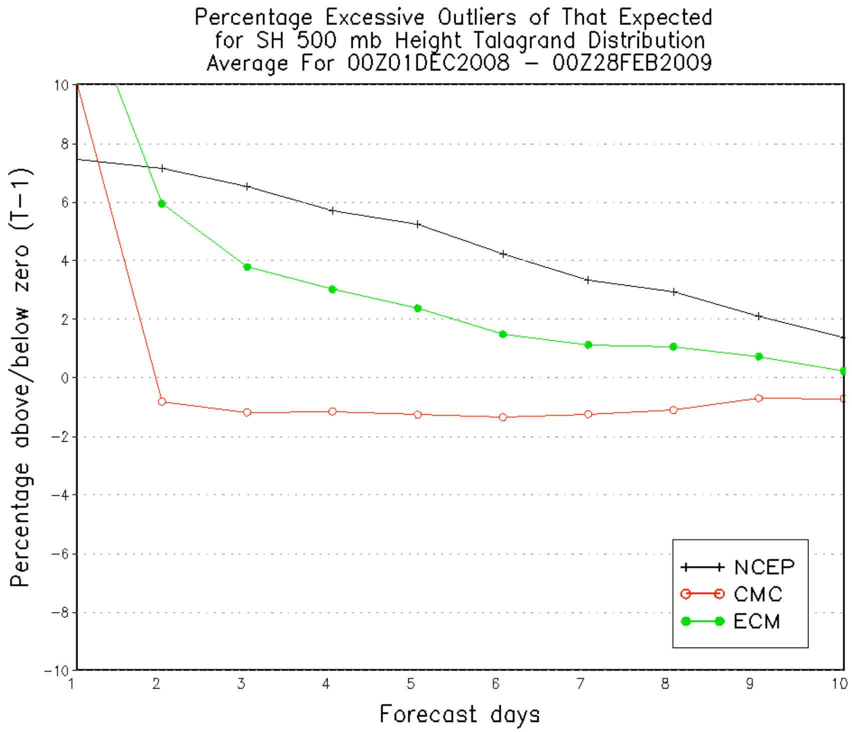


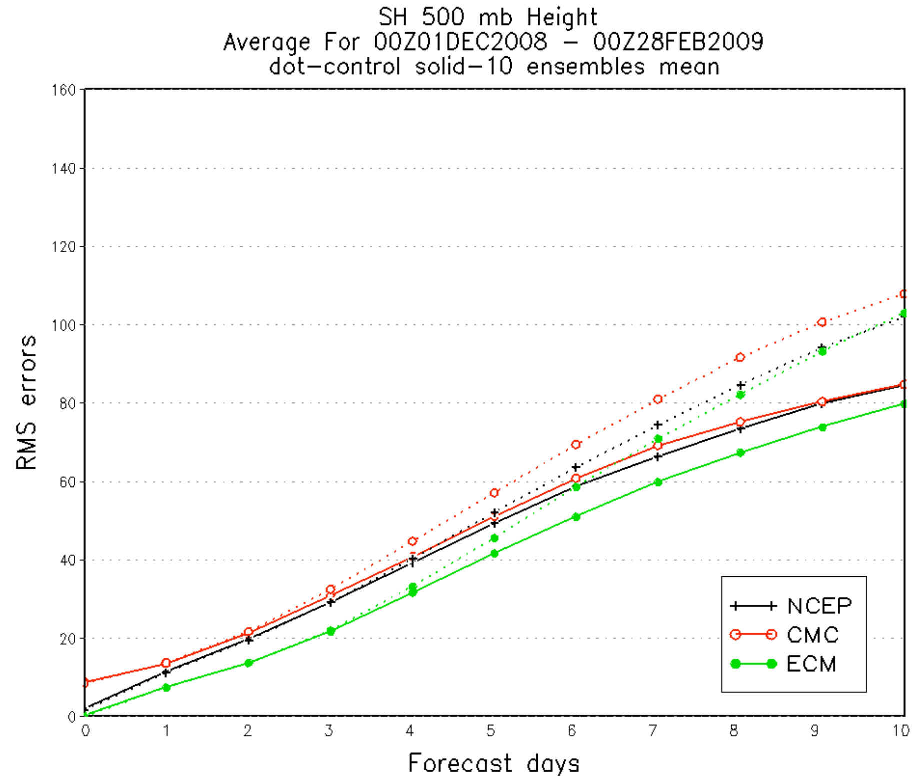
CLIMATE PROB	20%	20%	20%	20%	20%
FCST PROB	20%	40%	20%	20%	0%





EXAMPLE FOR 3 ENSEMBLES





- Canadian
  - Ensemble filter
    - Low time consistency between successive perturbations
    - Noise added to observations
- ECMWF
  - Singular vectors
    - Too low spread at short lead time
    - No time consistency between successive perturbations

- NCEP
  - Ensemble Transform
    - Strong time conistency
    - No noise added
  - No model related perturbations

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REQUIREMENTS, DEVELOPMENTS, & PLANS FOR PROBABILISTIC FORECAST APPLICATIONS

Zoltan Toth,
Isidora Jankov, Steve Albers, Paula McCaslin

Global Systems Division, ESRL/OAR/NOAA

Acknowledgements:
Stan Benjamin, Lynn Sherretz, Paul Schultz, Yuanfu Xie, Roman Krysztofowicz, Yuejian Zhu, Andre Methot, Tom Hamill, Kathy Gilbert, et al.

International Aviation Transportation Association (IATA) Met Task Force
September 27-29, 2010, Boulder, CO

OUTLINE / SUMMARY

- Sources of forecast errors
  - Initial condition – Observing system, DA
  - Model / ensemble formation

- How to assess forecast errors?
  - Error statistics from single forecasts – Statistical approach
  - Ensembles – Dynamical approach
  - Statistically post-processed ensembles – Dynamical-statistical approach

- Statistical post-processing of ensembles
  - Bias correction, merging, downscaling, derivation of variables

- Ensemble database
  - Summary statistics – Phase-1
  - Full ensemble data – Phase-2
  - All queries about weather can be answered

- Examples
  - Ensemble over West Coast of US (SF)
  - Display / decision tools

NUMERICAL WEATHER PREDICTION (NWP) BASICS

COMPONENTS OF NWP

- Create initial condition reflecting state of the atmosphere, land, ocean
- Create numerical model of atmosphere, land, ocean

ANALYSIS OF ERRORS

- Errors present in both initial conditions and numerical models
- Coupled atmosphere / land / ocean dynamical system is chaotic
  - Any error amplifies exponentially until nonlinearly saturated
  - Error behavior is complex & depends on
    - Nature of instabilities
    - Nonlinear saturation

IMPACT ON USERS

- Analysis / forecast errors negatively impact users
  - Impact is user specific (user cost / loss situation)
- Information on expected forecast errors needed for rational decision making
  - Spatial/temporal/cross-variable error covariance needed for many real life applications
  - How can we provide information on expected forecast errors?

WHAT INFORMATION USERS NEED

- General **characteristics of forecast users**
  - Each user *affected in specific way* by
    - *Various weather elements* at
    - *Different points in time &*
    - *Space*

- Requirements for **optimal decision making** for weather sensitive operation
  - Probability distributions for single variables
    - Lack of information on cross-correlations
  - Covariances needed across
    - Forecast variables, space, and time

- **Format of weather forecasts**
  - Joint probability distributions
    - Provision of all joint distributions possibly needed by users is intractable
  - Encapsulate best forecast info into calibrated ensemble members
    - Possible *weather scenarios*
      - 6-Dimensional Data-Cube (6DDC)
        - » 3 dimensions for space, 1 each for time, variable, and ensemble members

- **Provision of weather information**
  - Ensemble members for sophisticated users
    - Other types of format derived from ensemble data
  - All forecast information fully consistent with calibrated ensemble data

HOW CAN WE REDUCE & ESTIMATE EXPECTED FORECAST ERRORS?

STATISTICAL APPROACH

- Statistically assess errors in past unperturbed forecasts (eg, GFS, RUC)
  - Can correct for systematic errors in expected value
  - Can create probabilistic forecast information – Eg, MOS PoP
- Limitation
  - Case dependent variations in skill not captured
  - Error covariance information practically not attainable

DYNAMICAL APPROACH – Ensemble forecasting

- Sample initial & model error space - Monte Carlo approach
  - Leverage DTC Ensemble Testbed (DET) efforts
- Prepare multiple analyses / forecasts –
  - Case dependent error estimates
  - Error covariance estimates
- Limitation
  - Ensemble formation imperfect – not all initial / model errors represented

DYNAMICAL-STATISTICAL APPROACH

- Statistically post-process ensemble forecasts
  - Good of both worlds
  - How can we do that?

AVIATION EXAMPLE

- Recovery of a carrier from weather related disruptions
  - Operational decisions depend on multitude of factors
    - Based on United / Hemispheres March 2009 article, p. 11-12

- Factors affecting operations
  - *Weather –* multiple parameters
    - *Over large region / CONUS during coming few days*
  - Federal regulations / aircraft limitations
    - Dispatchers / load planners
  - Aircraft availability
    - Scheduling / flight planning
  - Maintenance
    - Pre-location of spare parts & other assets where needed
  - Reservations
    - Rebooking of passengers
  - Customer service
    - Compensation of severely affected customers

- How to design economically most viable operations?
  - Given goals / requirements / metrics / constraints

SELECTION OF OPTIMAL USER PROCEDURES

- Generate ensemble weather scenarios e_i, $i = 1, n$
- Assume weather is e_i, define optimal operation procedures o_i
- Assess cost/loss c_{ij} using o_i over all weather scenarios e_j
- Select o_i with minimum expected (mean) cost/loss $\underline{c}_{\underline{i}}$ over e_1,… e_n as optimum operation

COST/LOSS c_{ij} GIVEN e_j WEATHER & o_i OPERATIONS		ENSEMBLE SCENARIOS				EXPECTED COST
		e_1	e_2	.	e_n	
OPERATION PROCEDURES	o_1	c_{11}	c_{12}	.	c_n	$\underline{c}_{\underline{1}}$
	o_2	c_{21}	c_{22}	.	c_{2n}	$\underline{c}_{\underline{2}}$
	.	.	.	.	.	.
	o_n	c_{n1}	c_{n2}	.	c_{nn}	$\underline{c}_{\underline{n}}$

USER REQUIREMENTS FOR QUALITY

- Statistical resolution ("predictive skill")
  - Seek highest possible skill in ensemble of forecasts
  - Need to extract and fuse all predictive information
    - Ensembles, high resolution unperturbed forecasts, observations, etc

- Statistical reliability
  - Need to make ensemble members statistically indistinguishable from reality
    - Correct systematic errors (first moment correction)
    - Assess error statistics (higher moment corrections)
    - Use climatology as background information

FORECAST QUALITY - REALITY

Useful forecast info to ~20 days w. 20-80 km res. NWP models

- Imperfect models used
  - Model specific drift (lead-time dependent systematic error)
    - Need unconditional bias correction of each member on model grid
      - Solution, eg: ***Bayesian Pre-Processor*** (BPP)
- Imperfect ensemble formation
  - Forecasts are correlated, have various levels of skill, and form uncalibrated cfd (spread)
    - Need to optimally fuse all predictive info into calibrated posterior cdf
      - Solution, eg: ***Bayesian Processor of Ensembles*** (BPE)
- Stat. post-processing works on distribution of variables
  - Raw ensemble members inconsistent with posterior cdf
    - Need to adjust ensemble members to be consistent with posterior cdf
      - Solution, eg: ***Members "mapped" into posterior quantiles***
- NWP models don't resolve variables of interest to user
  - Information missing on fine time/spatial scales, further vars.
    - Need to relate NWP forecast info to user variables
      - Solution, eg: ***Bayesian downscaling*** to fine resolution grid

STATISTICAL POST-PROCESSING

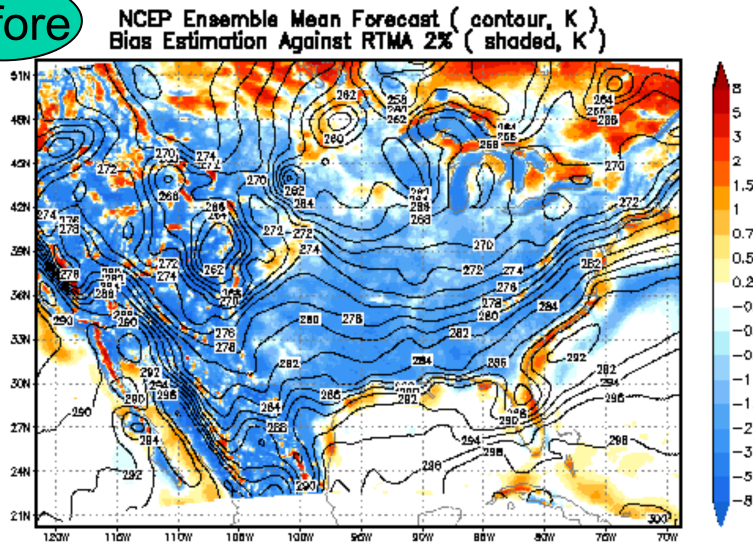
- Problem
  - Relate coarse resolution biased forecast to user relevant fine resolution information
- Tasks broken up to facilitate collaboration / transition to operations
  - Bias correct coarse resolution ensemble grid wrt NWP analysis
    - Cheap
    - Sample of forecasts / hind-casts needed
  - Merge various guidance
    - Fuse all predictive info into “unified ensemble”
  - Create observationally based fine resolution analysis
    - Estimate of truth
  - Downscale bias-corrected ensemble forecast
    - Relate coarse resolution NWP and fine resolution observationally based analyses
      - Perfect prog approach - No need for hind-casts
  - Derive additional variables – AIVs
    - Based on bias corrected & downscaled ensemble
- Outcome
  - Skillful and statistically reliable ensemble of AIV variables on fine grid

00hr GEFS Ensemble Mean & Bias Before/After Downscaling 10%

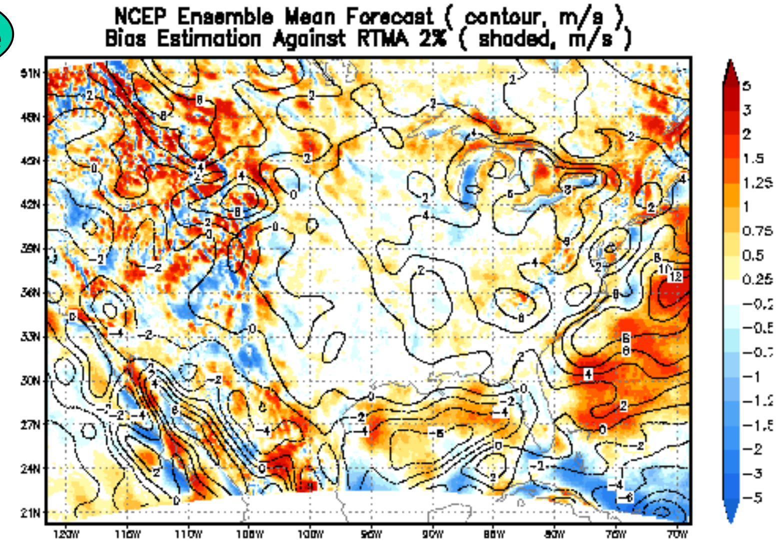
2m Temperature

10m U Wind

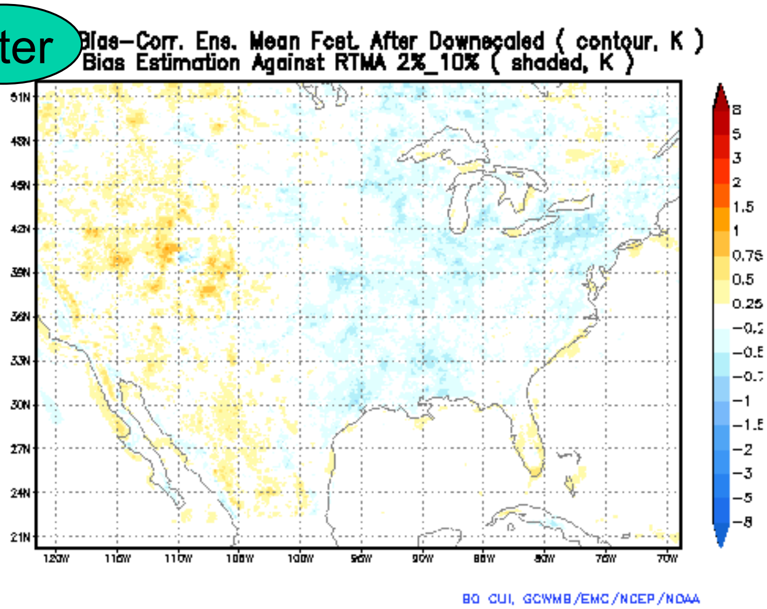
Before



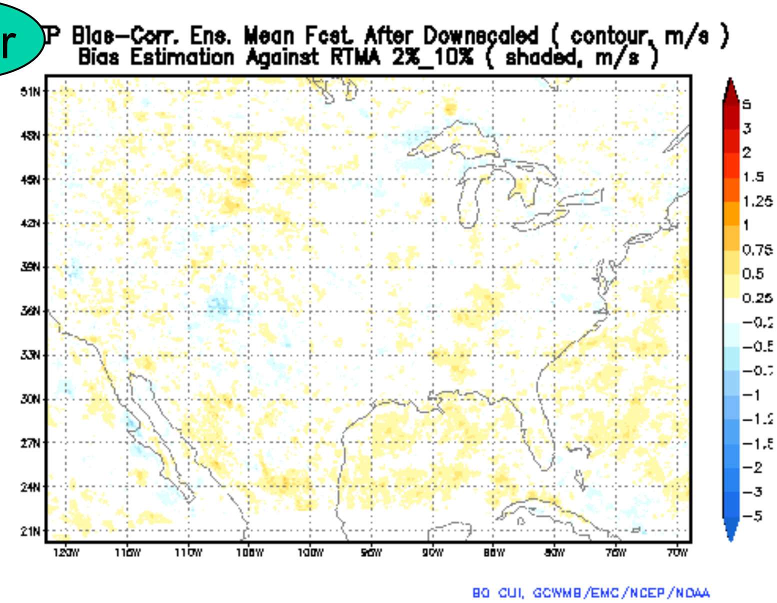
Before



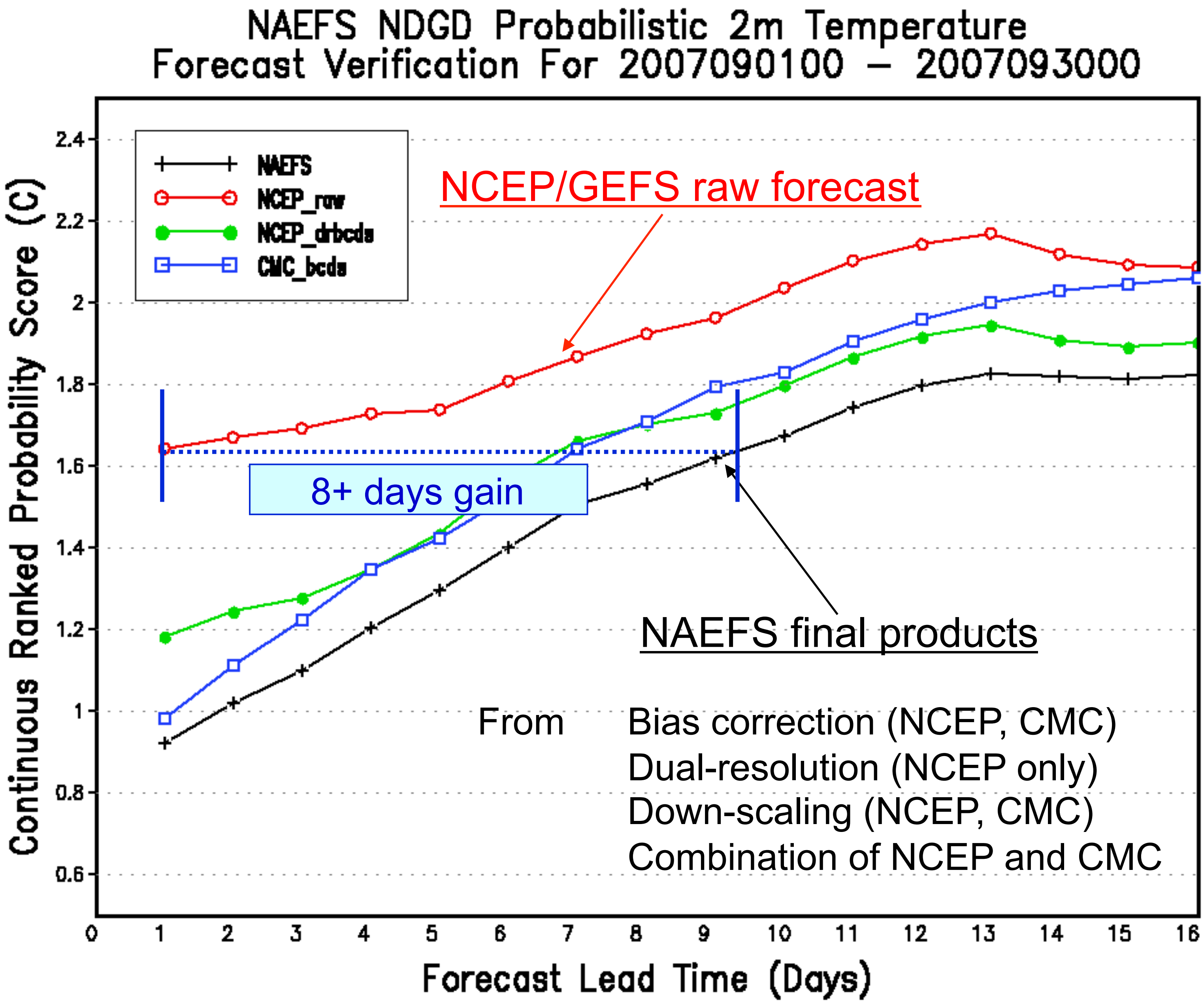
After



After



CONTINUOUS RANKED PROBABILITY SCORE
RAW / BIAS CORR. & DOWNSCALED & HIRES MERGED / NAEFS



High resolution control & Canadian ensemble adds significant value

=>

8-day total gain in skill

ENSEMBLE DATABASE

- **Depository / access**
  - Create unified NOAA digital ensemble forecast database
    - Summary statistics from ensemble
      - E.g., 10/50/90 percentile forecasts - Pase 1
    - All ensemble members
      - E.g., 20-100 members - Phase 2
  - Provide easy access to internal / external users
    - Seamless forecasts across lead time ranges
    - Many applications beyond NEXTGEN
  - Part of 4D-Cube
    - Relationship with SAS?

- **Interrogation / forecaster tools**
  - Modify summary statistics
  - Back-propagate modified information into ensemble
  - Derive ***any*** information from summary statistics / ensembles
    - ***All queries about weather can be answered***
      - Joint probabilities, spatial/temporal aggregate variables, etc

Ensemble Prediction System Development for Aviation and other Applications

Isidora Jankov[1], Steve Albers[1], Huiling Yuan[3], Linda Wharton[2], Zoltan Toth[2], Tim Schneider[4], Allen White[4] and Marty Ralph[4]

[1]Cooperative Institute for Research in the Atmosphere (CIRA),
Colorado State University, Fort Collins, CO
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[2]NOAA/ESRL/Global Systems Division

[3]Cooperative Institute for Research in Environmental Sciences (CIRES)
University of Colorado, Boulder, CO
Affiliated with NOAA/ESRL/Global Systems Division

[4] NOAA/ESRL/Physical Sciences Division

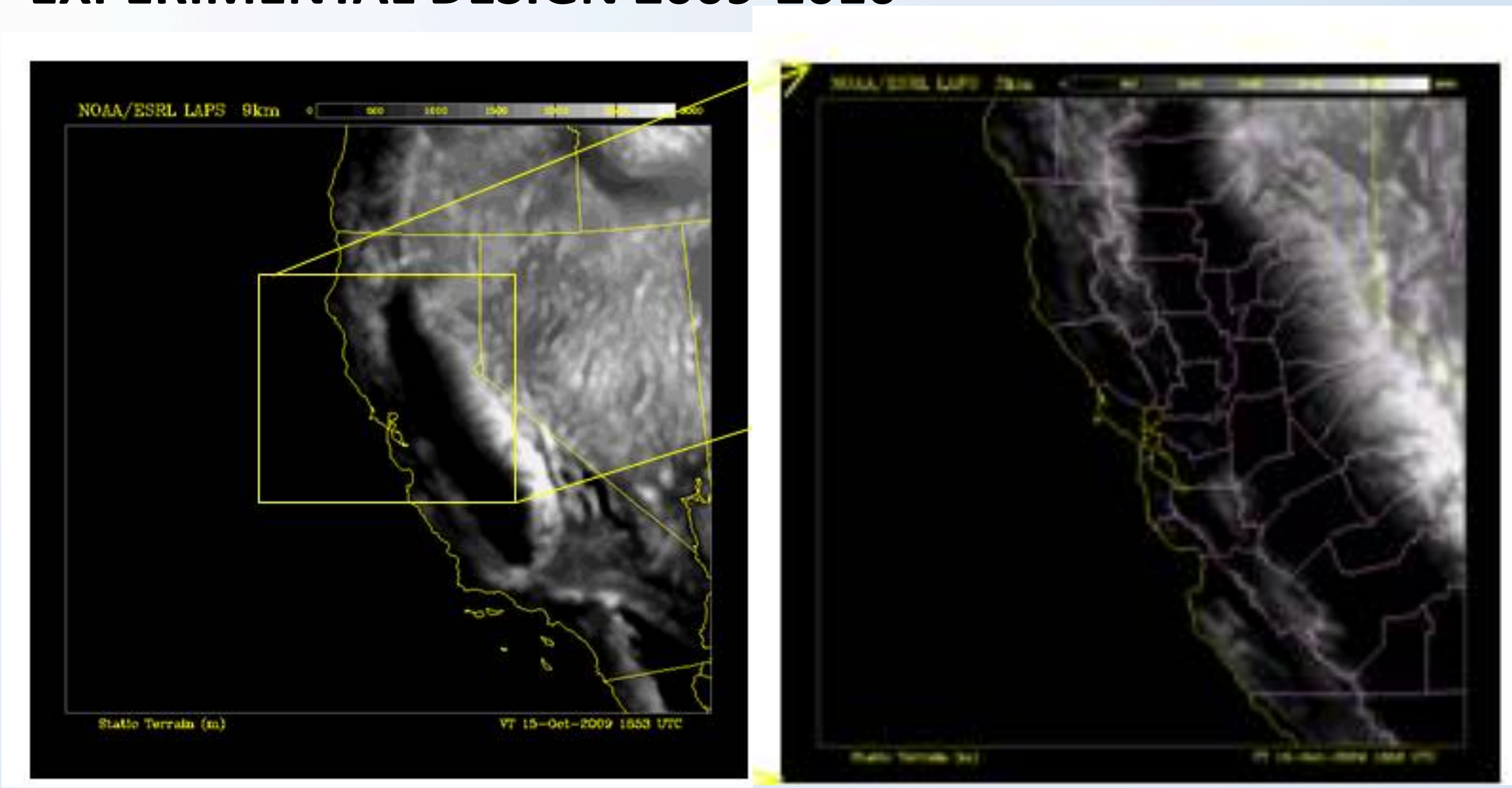
BACKGROUND

- Objective
  - Develop fine scale ensemble forecast system

- Application areas
  - Aviation (SF airport)
  - Winter precipitation (CA & OR coasts)
  - Summer fire weather (CA)

- Potential user groups
  - Aviation industry, transportation, emergency and ecosystem management, etc

EXPERIMENTAL DESIGN 2009-2010



Nested domain:

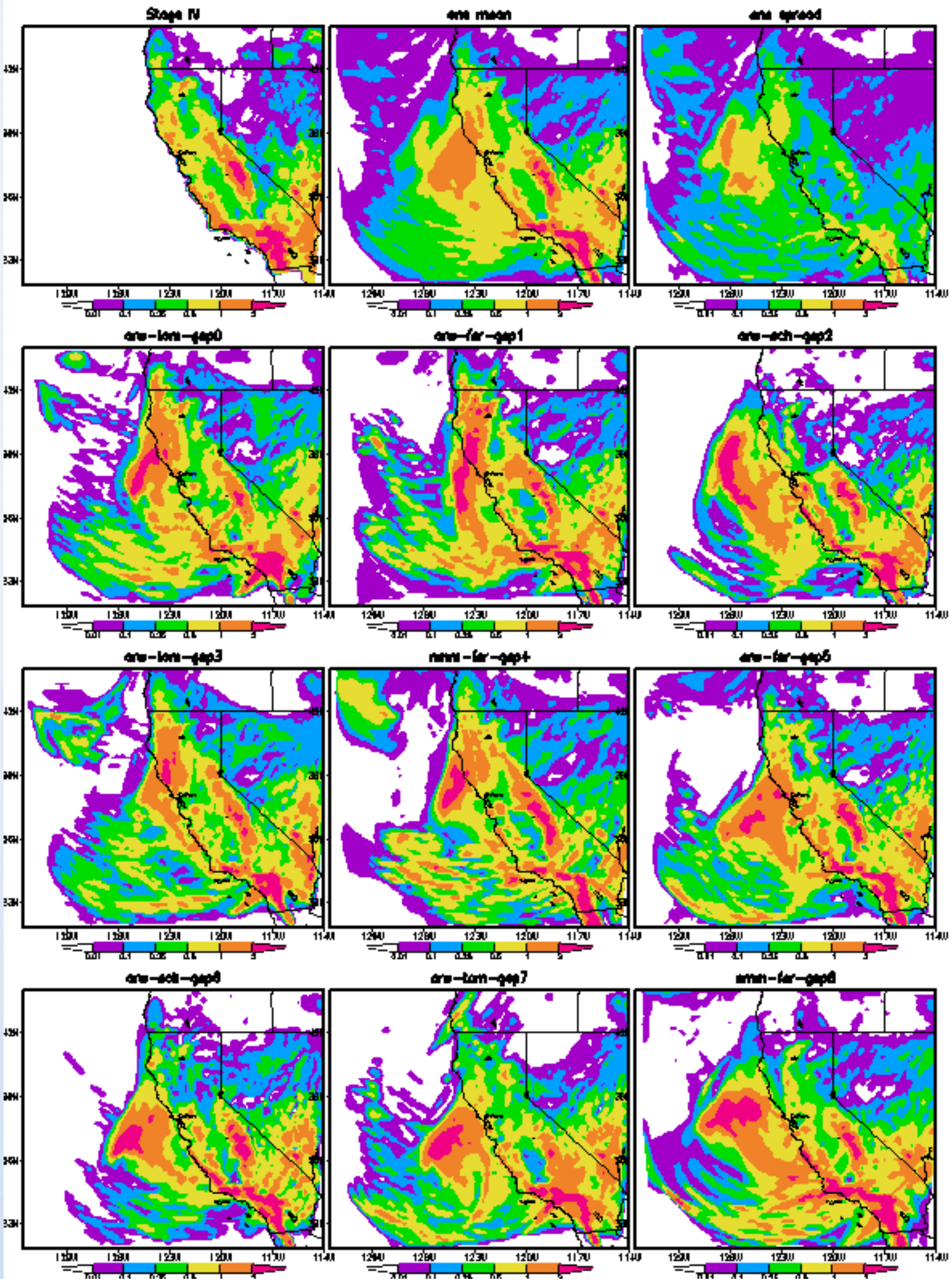
- Outer/inner nest grid spacing 9 and 3 km, respectively.
- 6-h cycles, 120hr forecasts foe the outer nest and 12hr forecasts for the inner nest
- 9 members (listed in the following slide)
- Mixed models, physics & perturbed boundary conditions from NCEP Global Ensemble

- 2010-2011 season everything stays the same except initial condition perturbations?

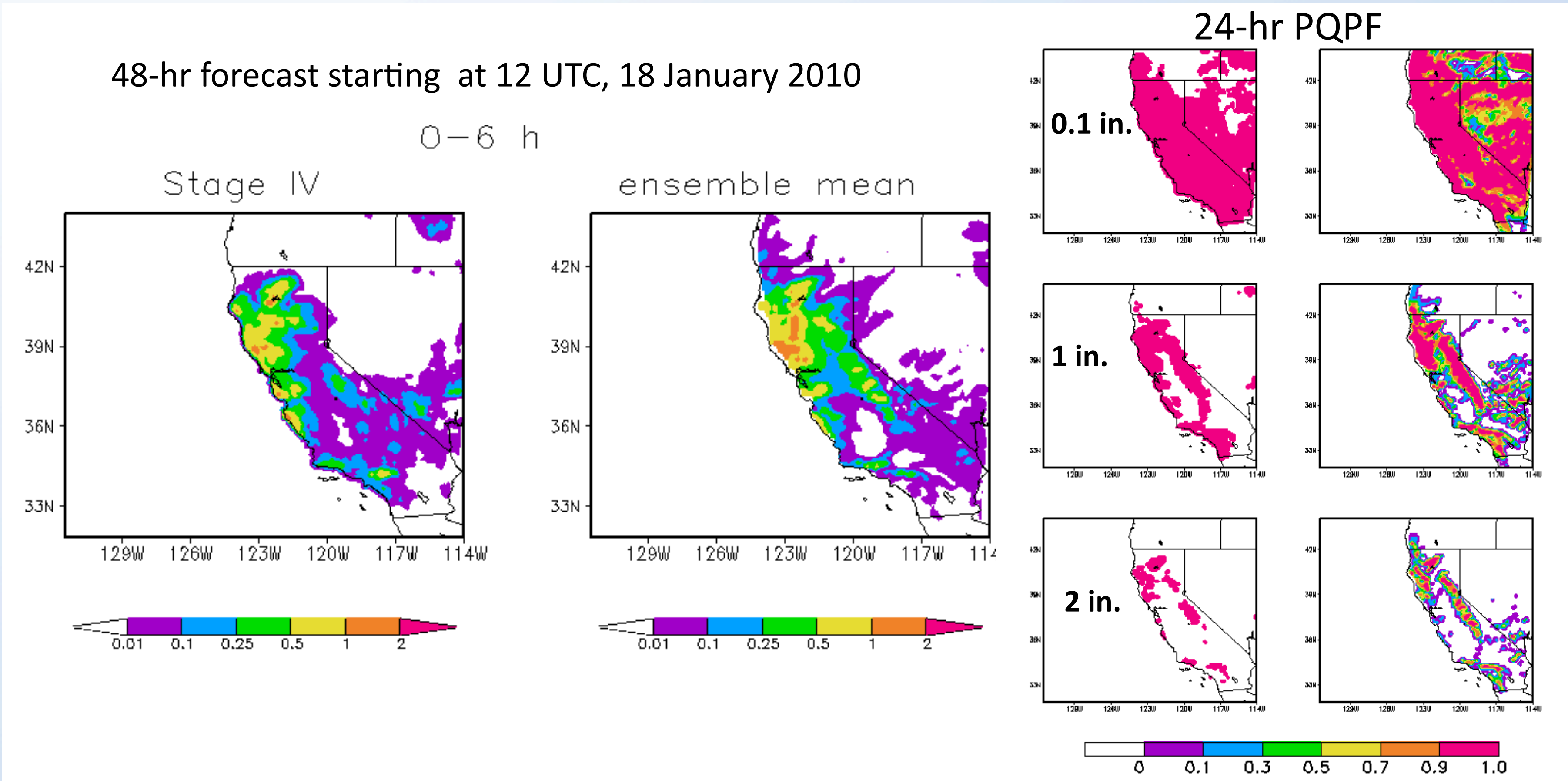
QPF

Example of 24-h QPF
9-km resolution

9 members:
ARW-TOM-GEP0
ARW-FER-GEP1
ARW-SCH-GEP2
ARW-TOM-GEP3
NMM-FER-GEP4
ARW-FER-GEP5
ARW-SCH-GEP6
ARW-TOM-GEP7
NMM-FER-GEP8



HMT QPF and PQPF

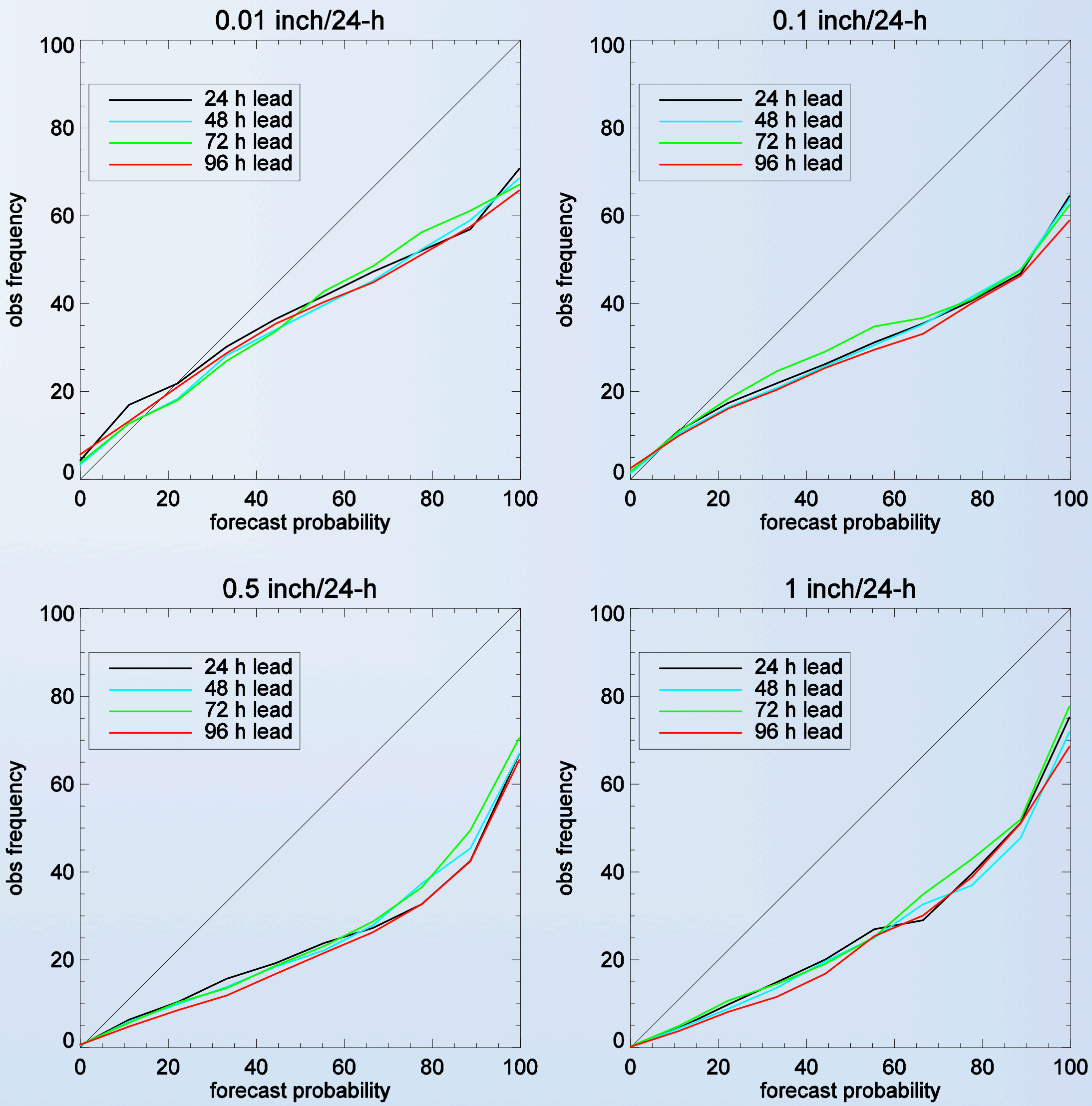


Reliability of 24-h PQPF

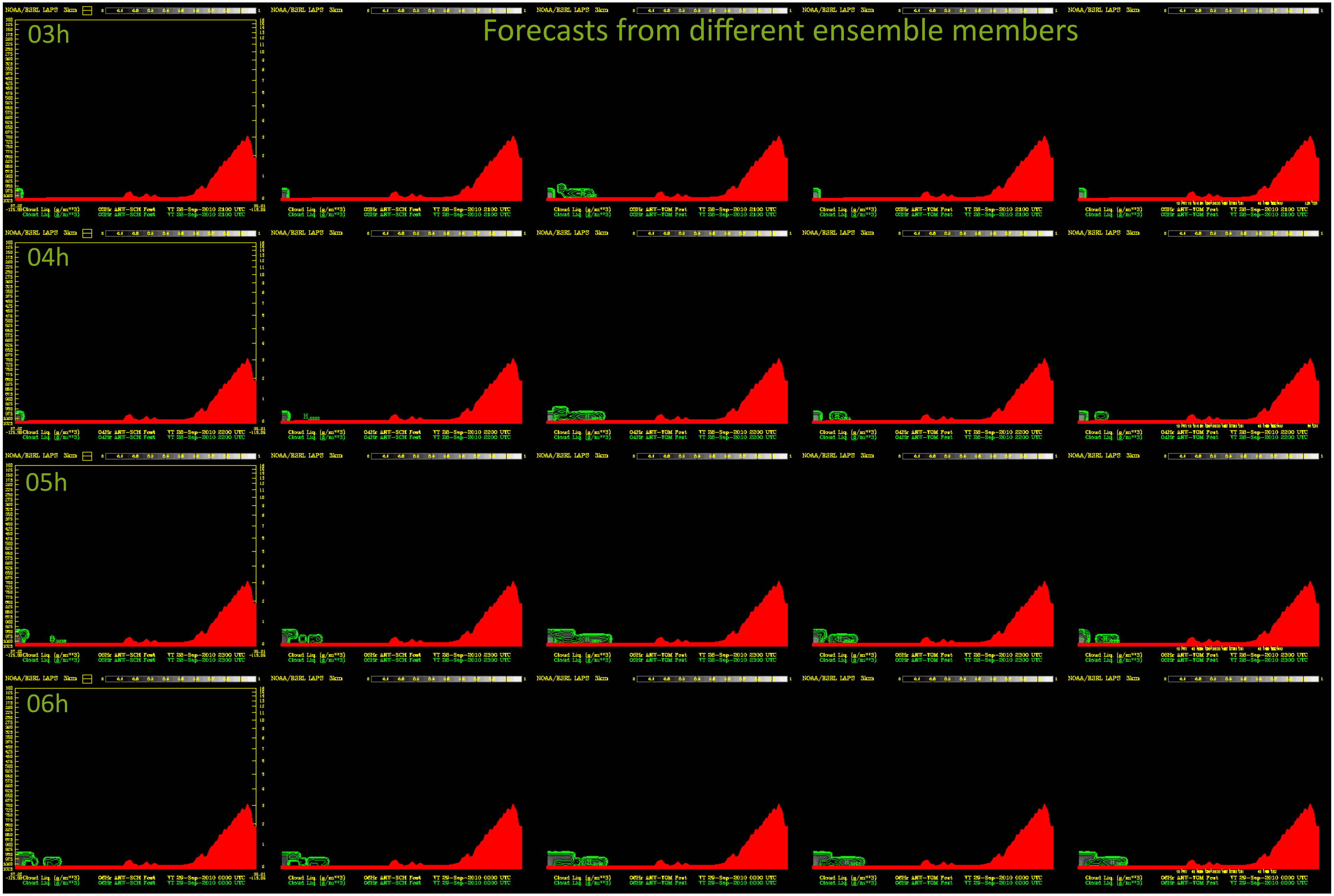
Reliability diagrams of 24-h PQPF
9-km resolution
Dec 2009 - Apr 2010

Observed frequency vs forecast probability
Overforecast of PQPF
Similar performance for different lead times

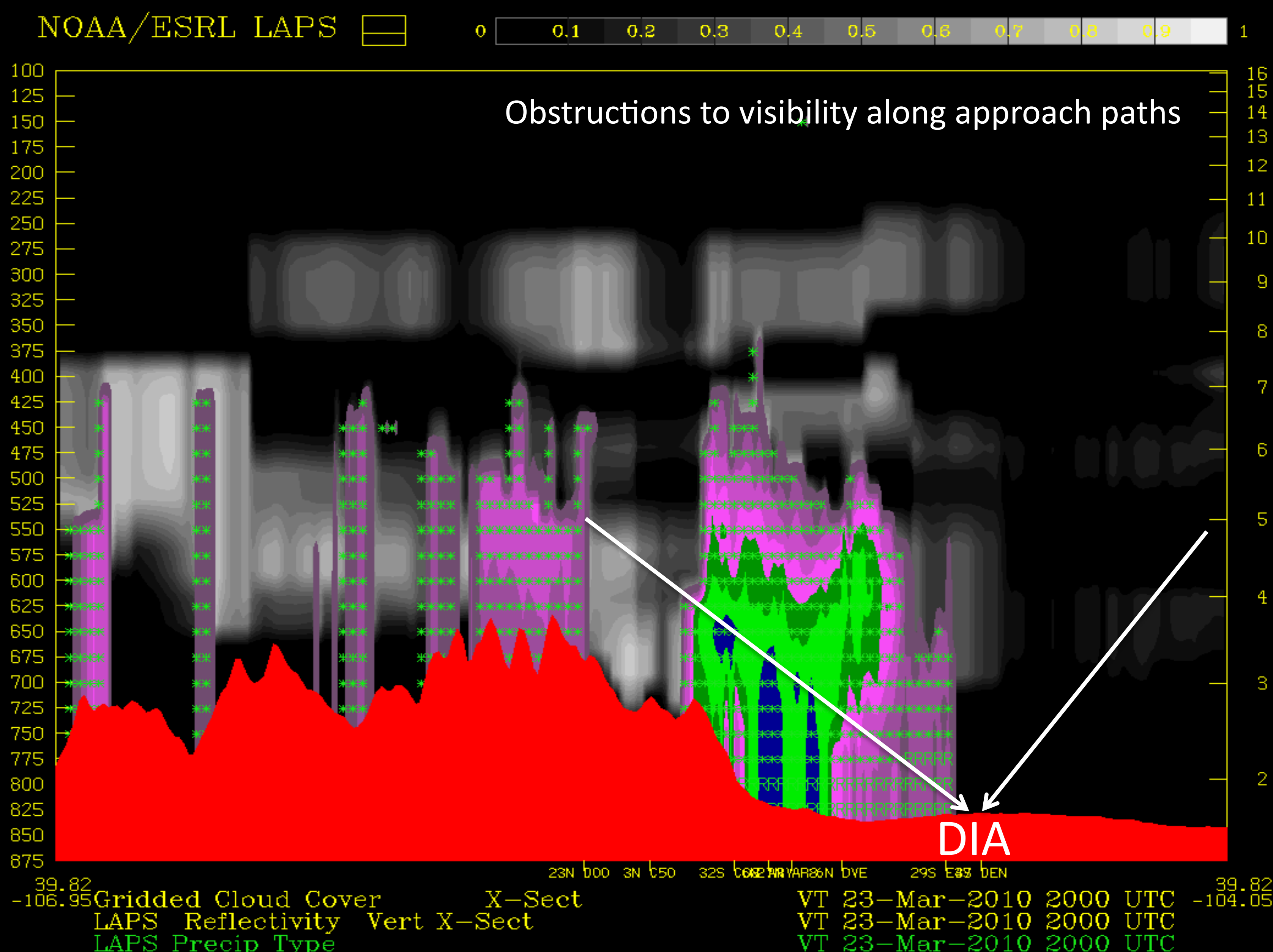
Brier skill score (BSS):
Reference brier score is Stage IV sample climatology
BSS is only skilful for 24-h lead time at all thresholds and for 0.01 inch/24-h beyond 24-h lead time.



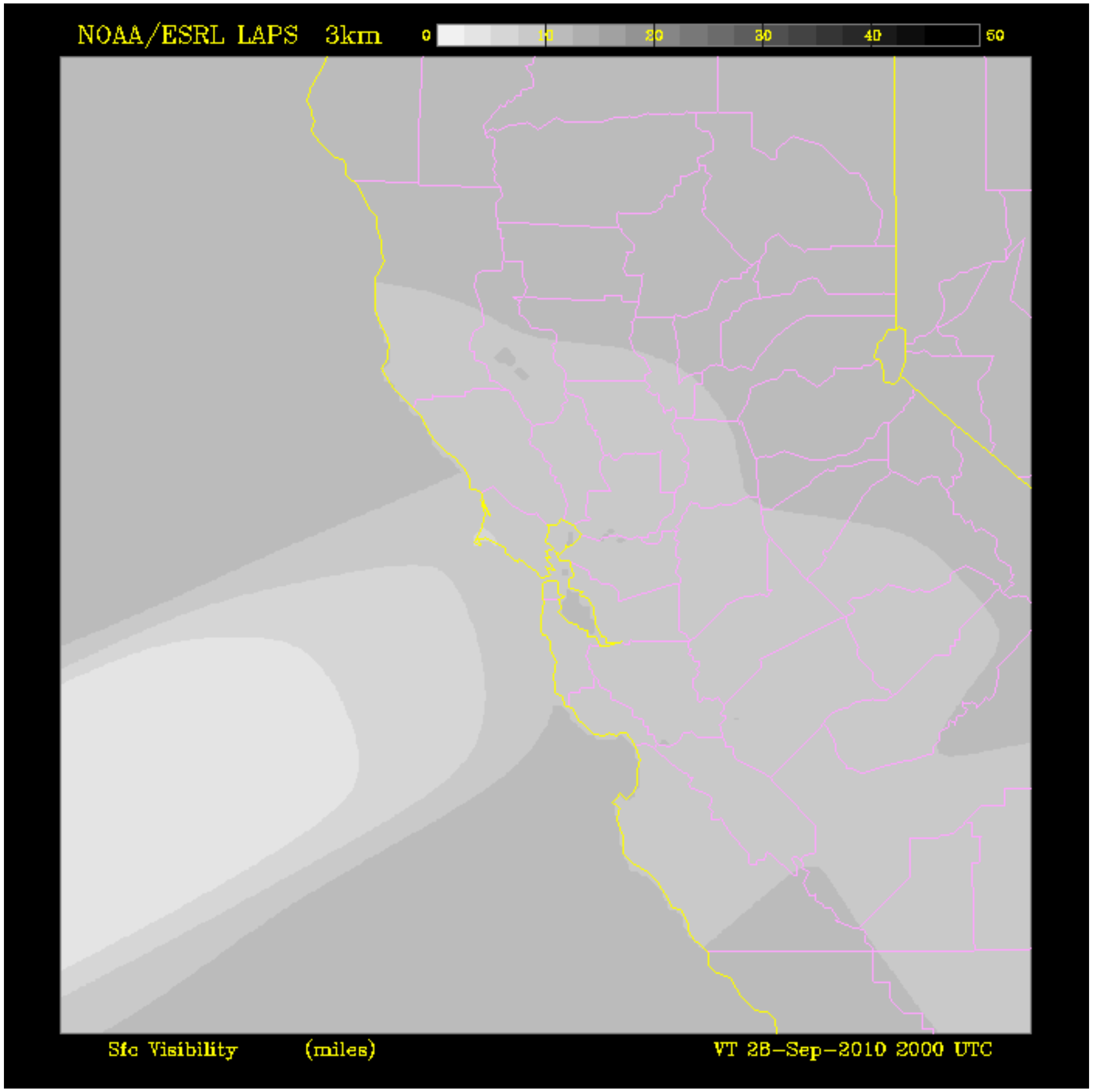
West-East XCs of Cloud Liquid through the San Francisco Area for Model runs initialized on 28 Sept. 2010 at 18UTC



Cloud / Reflectivity / Precip Type (1km analysis)



Analysis of Visibility for the period 18 UTC 28 Sept. 2010 to 00UTC 29 Sept. 2010



Paula McCaslin and Kirk Holub, NOAA Earth Systems Research Laboratory

GSD Initiative

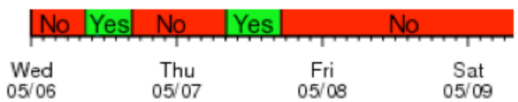
- Exploratory web-based decision support tool
- Decision guidance based on individual requirements for a given activity, in weather sensitive situations
- Risk assessment interface, including economic (cost-loss) module
- Risk tolerance affects Yes/No decision guidance by associating (calibrated) forecast uncertainty and risk limits
- Results created on demand

Earth System Research Laboratory
Personal Weather Advisor (PWA)

Home | Thresholds | Risks | Preferences | Contact

Decision Support in Weather Sensitive Situations

Yes/No Decision Guidance for a planned activity

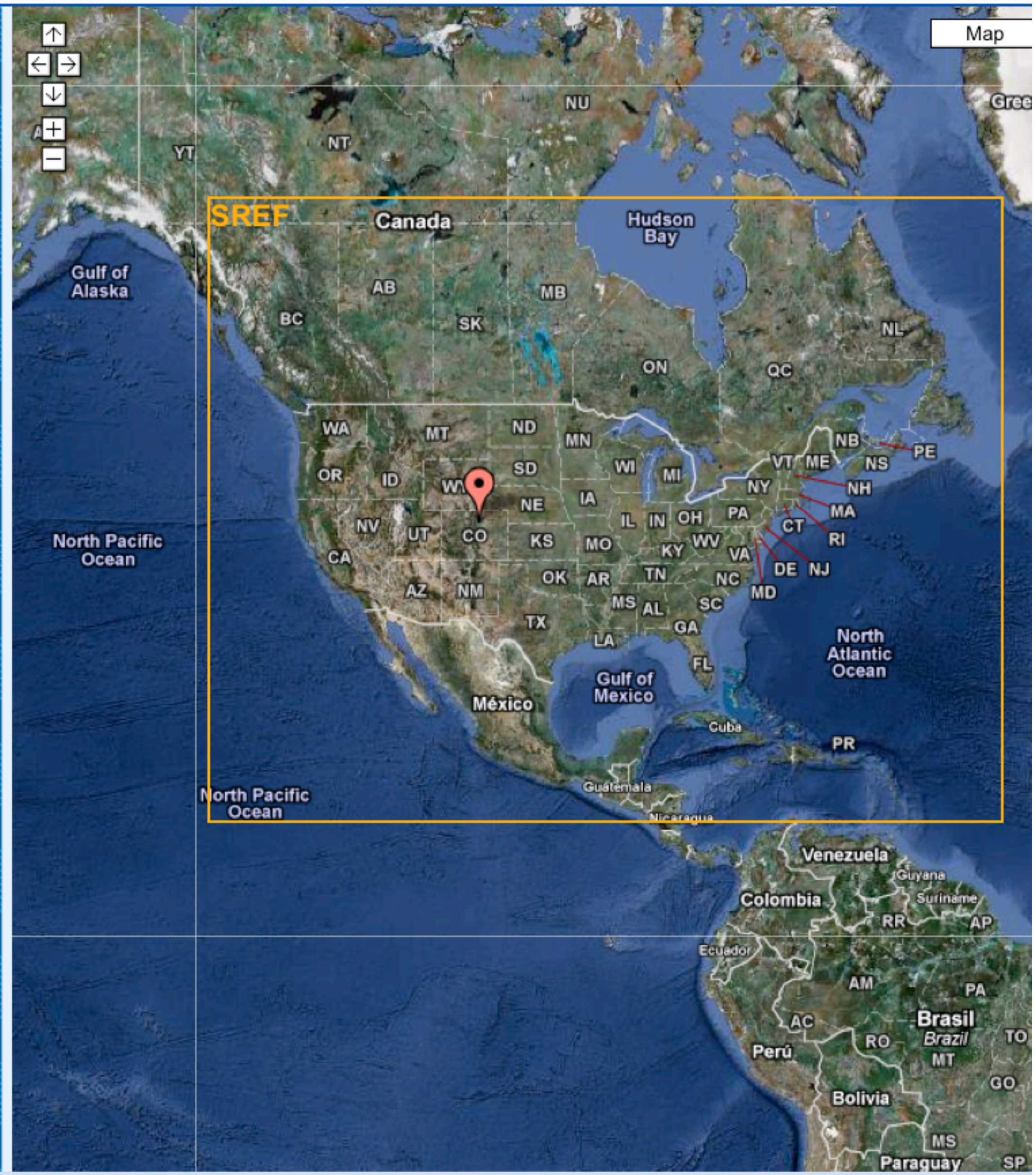


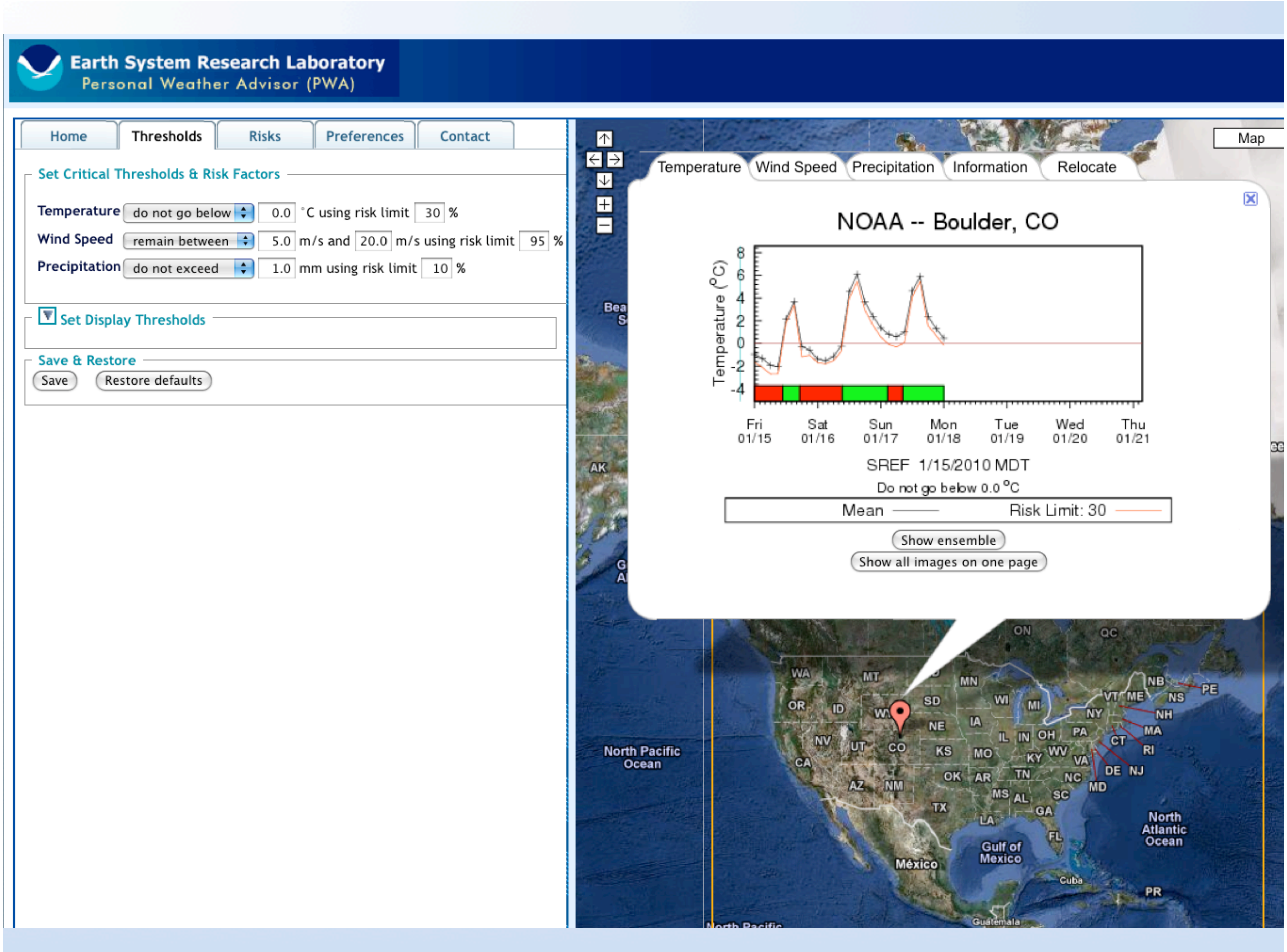
Welcome to the **Personal Weather Advisor** (PWA). Click on the Thresholds tab above to enter the range of weather parameters required for your activity. Then, **Save** the information and click on Google Maps™ for a location marker in the area you are interested in.

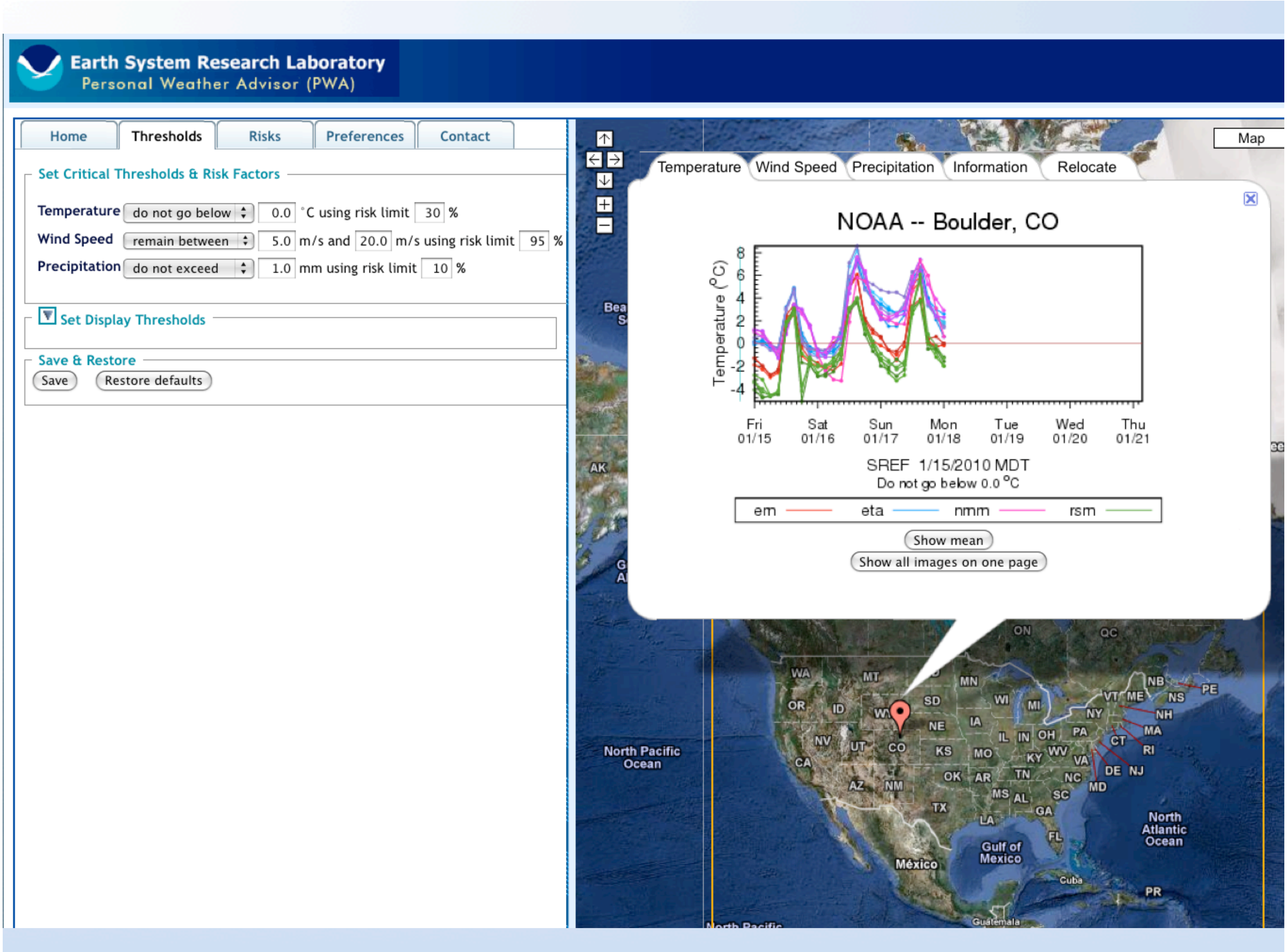
PWA gives you guidance on your activitiy based on the associated risk limit you are willing to take. Click on the Risks tab above for help assessing the risk you are willing to take for your activity.

This will query the forecast grids to find when your weather requirements will be met at the nearest grid point over the next 5 days giving you a Yes or No answer.

This application generates products from a ensemble forecast data base. It is intended to allow a user to define and produce a forecast for general planning purposes only. Customers are urged to obtain the latest official forecast information prior to engaging in any weather sensitive activity, and to monitor forecasts for updates during such activities.




Earth System Research Laboratory
Personal Weather Advisor (PWA)
Home
Thresholds
Risks
Preferences
Contact
Set Critical Thresholds & Risk Factors
Temperature do not go below 0.0 °C using risk limit 30 %
Wind Speed remain between 5.0 m/s and 20.0 m/s using risk limit 95 %
Precipitation do not exceed 1.0 mm using risk limit 10 %
Set Display Thresholds
Save & Restore
Save
Restore defaults
Map
Temperature
Wind Speed
Precipitation
Information
Relocate
NOAA -- Boulder, CO
Temperature (°C)
Fri 01/15
Sat 01/16
Sun 01/17
Mon 01/18
Tue 01/19
Wed 01/20
Thu 01/21
SREF 1/15/2010 MDT
Do not go below 0.0 °C
Mean
Risk Limit: 30
Show ensemble
Show all images on one page
North Pacific Ocean
North Atlantic Ocean
Gulf of Mexico
México
Cuba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Set Display Thresholds
Save & Restore
Save
Restore defaults
Map
Temperature
Wind Speed
Precipitation
Information
Relocate
NOAA -- Boulder, CO
Temperature (°C)
8
6
4
2
0
-2
-4
Fri 01/15
Sat 01/16
Sun 01/17
Mon 01/18
Tue 01/19
Wed 01/20
Thu 01/21
SREF 1/15/2010 MDT
Do not go below 0.0 °C
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eta
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rsm
Show mean
Show all images on one page
North Pacific Ocean
North Atlantic Ocean
Gulf of Mexico
México
Cuba
AK
ON
QC
WA
MT
OR
ID
WY
SD
MN
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TX
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FL
PR

OUTLINE / SUMMARY

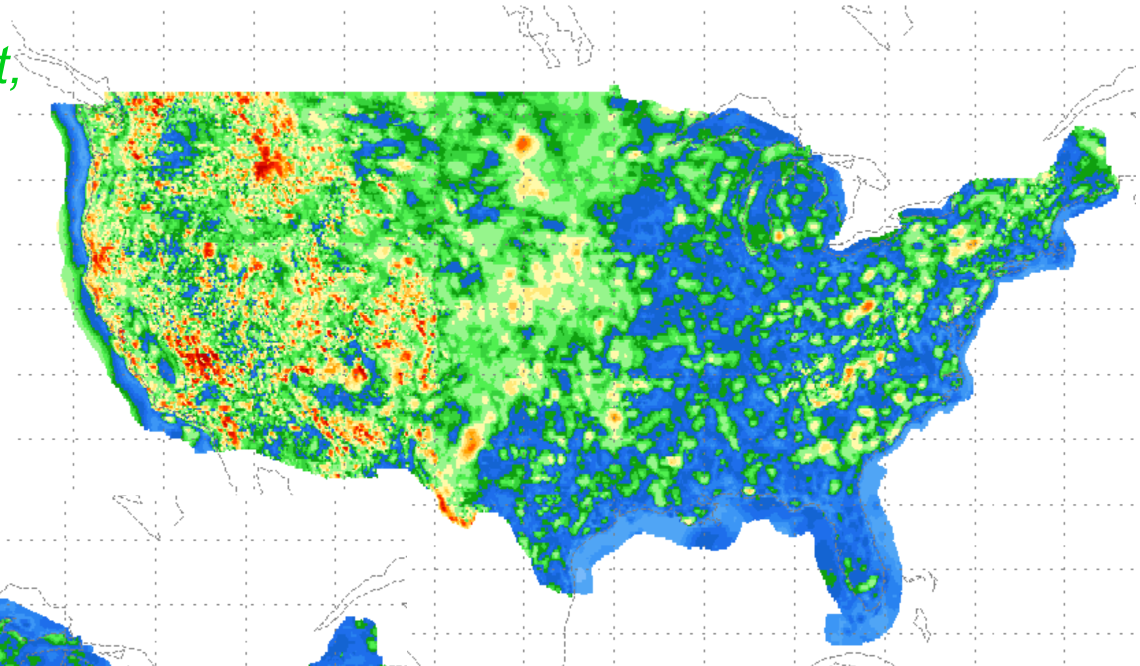
- Sources of forecast errors
  - Initial condition – Observing system, DA
  - Model / ensemble formation
- How to assess forecast errors?
  - Error statistics from single forecasts – Statistical approach
  - Ensembles – Dynamical approach
  - Statistically post-processed ensembles – Dynamical-statistical approach
- Statistical post-processing of ensembles
  - Bias correction, merging, downscaling, derivation of variables
- Ensemble database
  - Summary statistics – Phase-1
  - Full ensemble data – Phase-2
  - All queries about weather can be answered
- Examples
  - Ensemble over West Coast of US (SF)
  - Display / decision tools

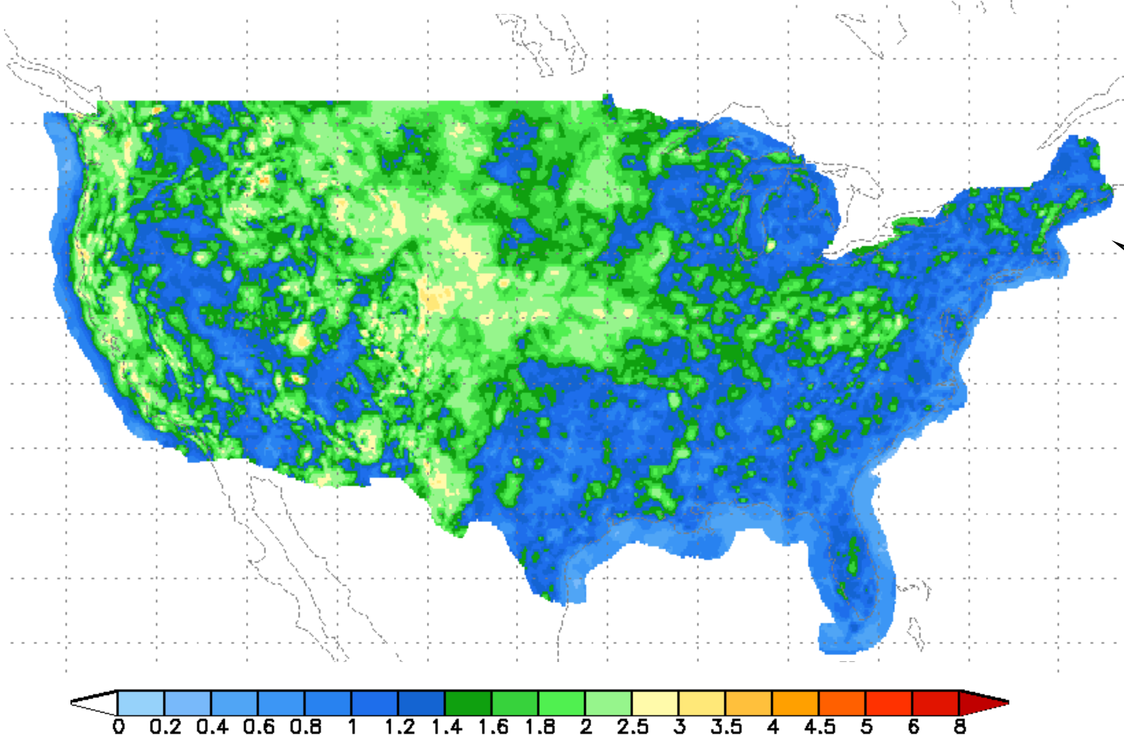
BACKGROUND

MDL GMOS & NAEFS Downscaled Forecast
Mean Absolute Error w.r.t. RTMA Average For Sept. 2007

Valery Dagostaro, Kathy Gilbert,
Bo Cui, Yuejian Zhu

24-h GMOS
Forecast



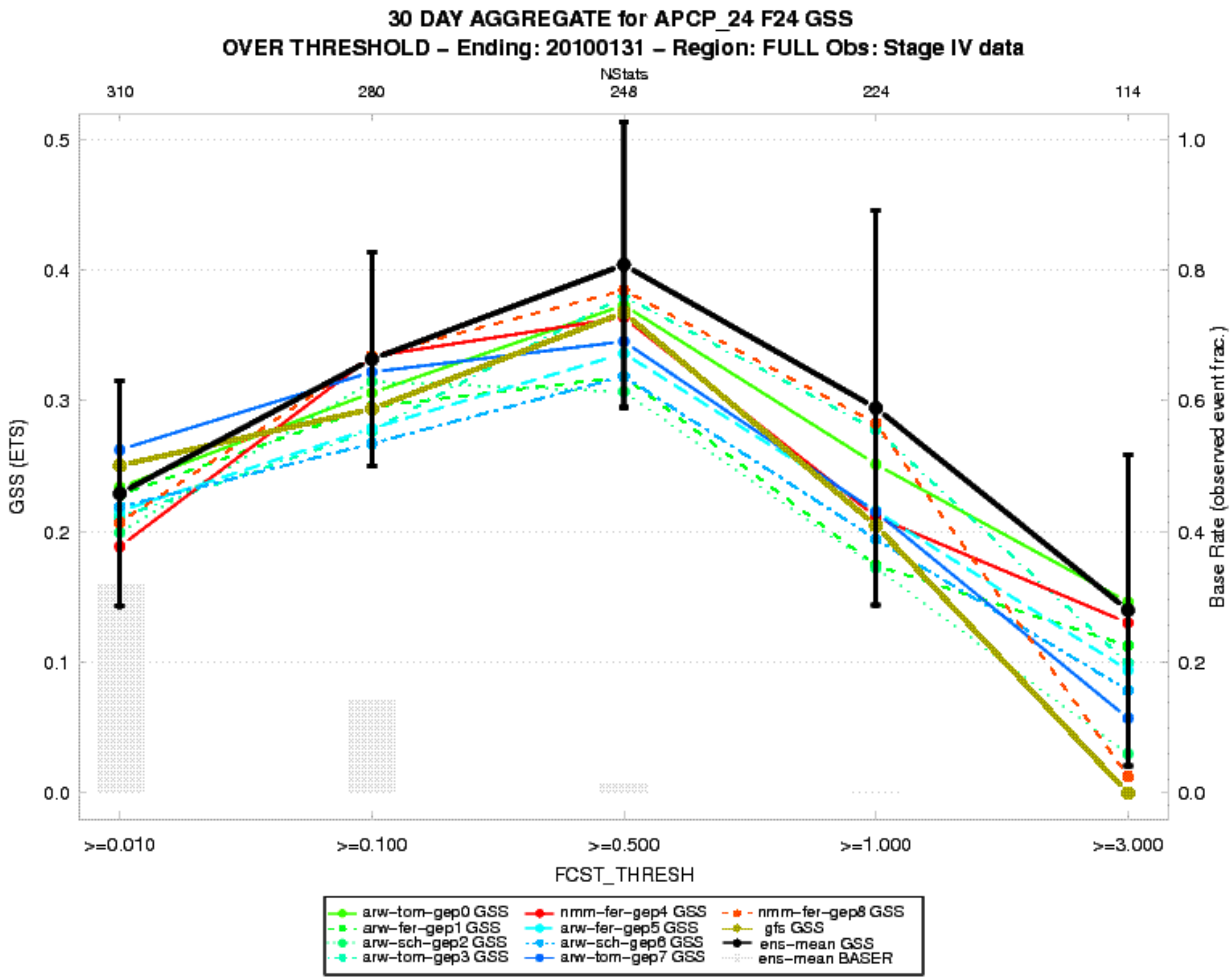


24-h NAEFS
Forecast

For CONUS:

NAEFS(1.45) : GMOS(1.72)

19% impr. over GMOS



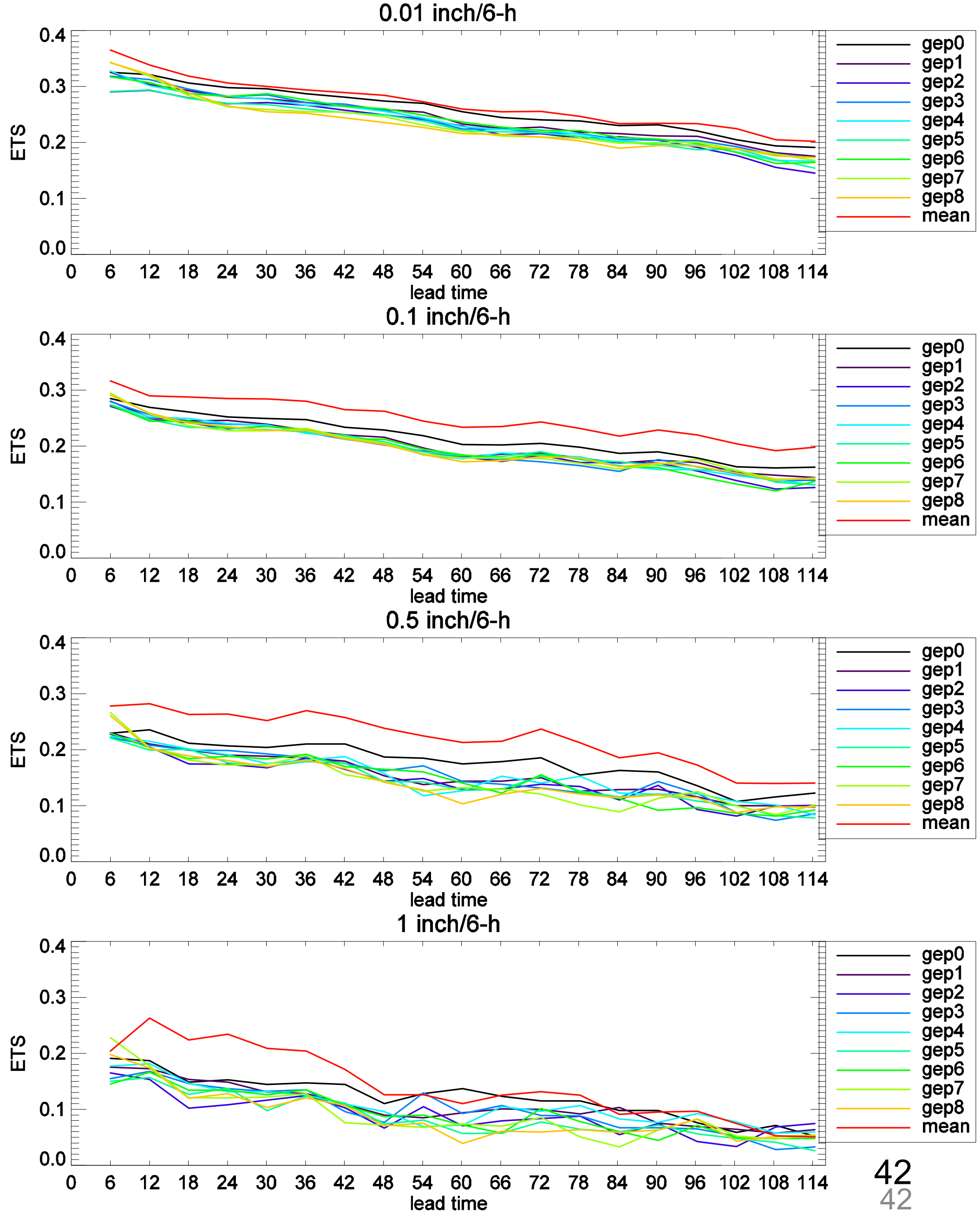
30 DAY AGGREGATE for APCP_24 F24 GSS
OVER THRESHOLD – Ending: 20100131 – Region: FULL Obs: Stage IV data
NStats
310
280
248
224
114
GSS (ETS)
Base Rate (observed event frac.)
0.0
0.1
0.2
0.3
0.4
0.5
0.0
0.2
0.4
0.6
0.8
1.0
>=0.010
>=0.100
>=0.500
>=1.000
>=3.000
FCST_THRESH
arw–tom–gep0 GSS
arw–fer–gep1 GSS
arw–sch–gep2 GSS
arw–tom–gep3 GSS
nmm–fer–gep4 GSS
arw–fer–gep5 GSS
arw–sch–gep6 GSS
arw–tom–gep7 GSS
nmm–fer–gep8 GSS
gfs GSS
ens–mean GSS
ens–mean BASER

ETS of 6-h QPF

Equitable threat score (ETS) of 6-h QPF
9-km resolution
Dec 2009 - Apr 2010 (some missing data)
Verification data: Stage IV

6-h QPF verified 4 times per day (00, 06, 12, 18 UTC)
6-114 h lead times

Ensemble mean is much better than individual members.
Gep0 (control) is also better.



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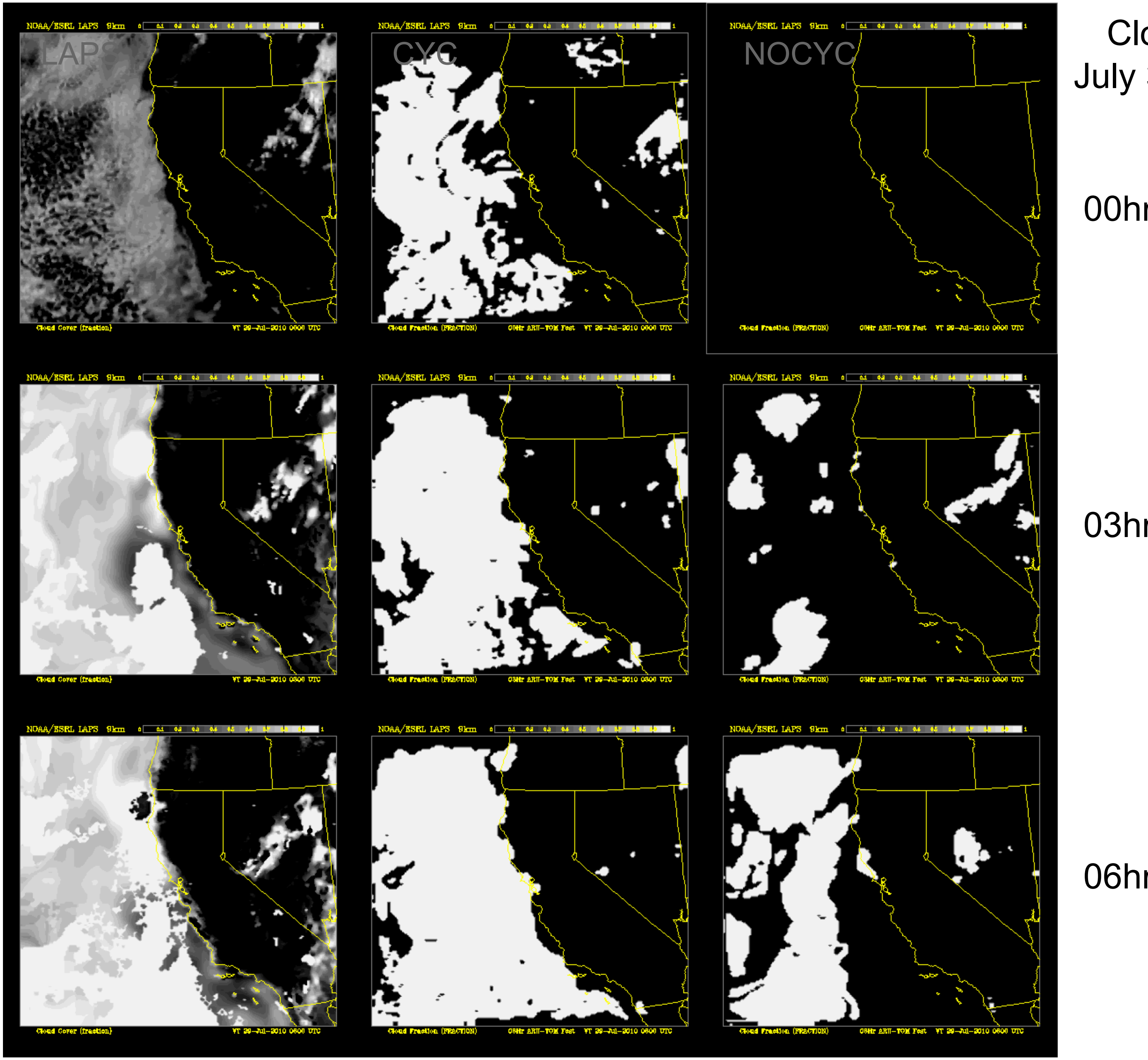
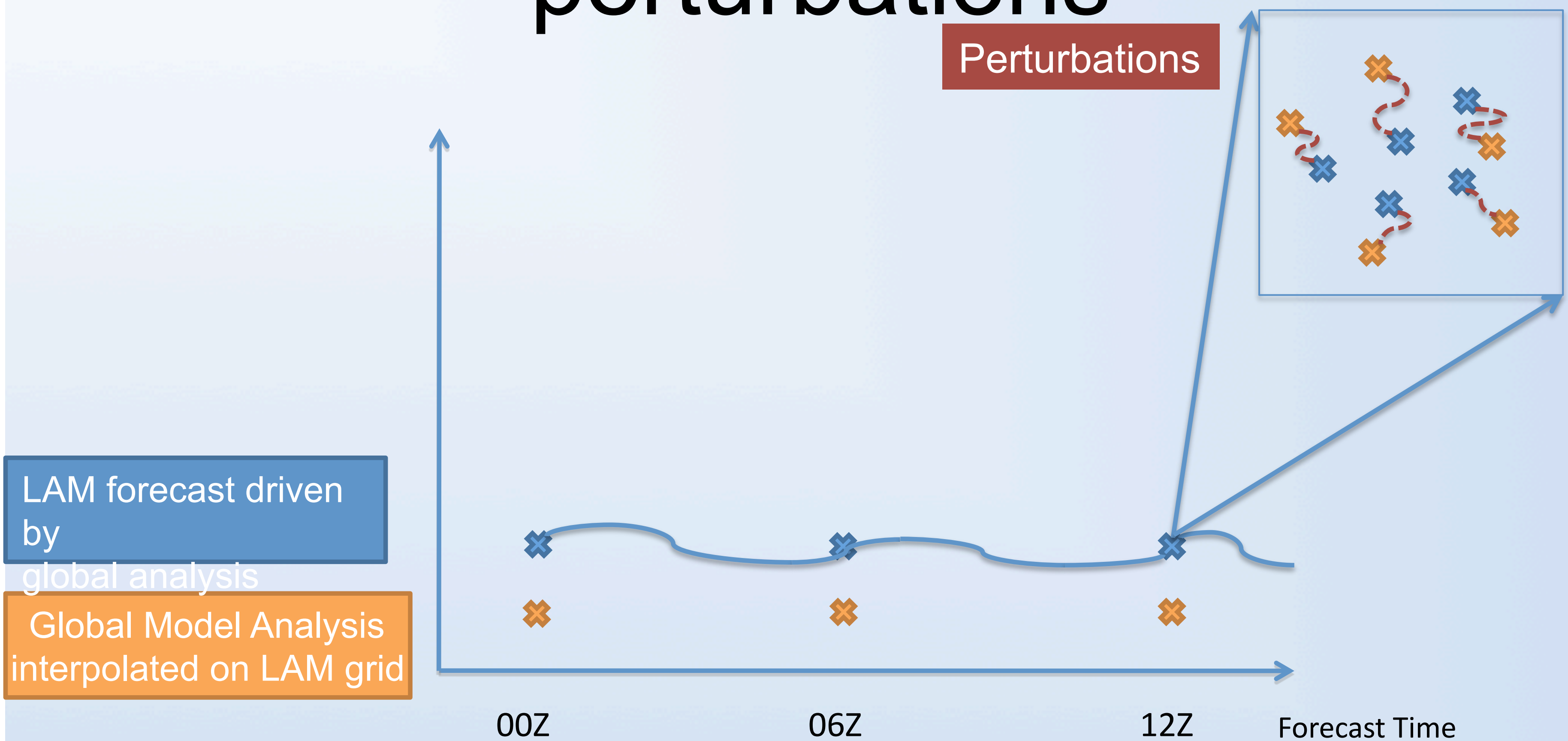
Cloud Coverage
July 30 2010 00UTC



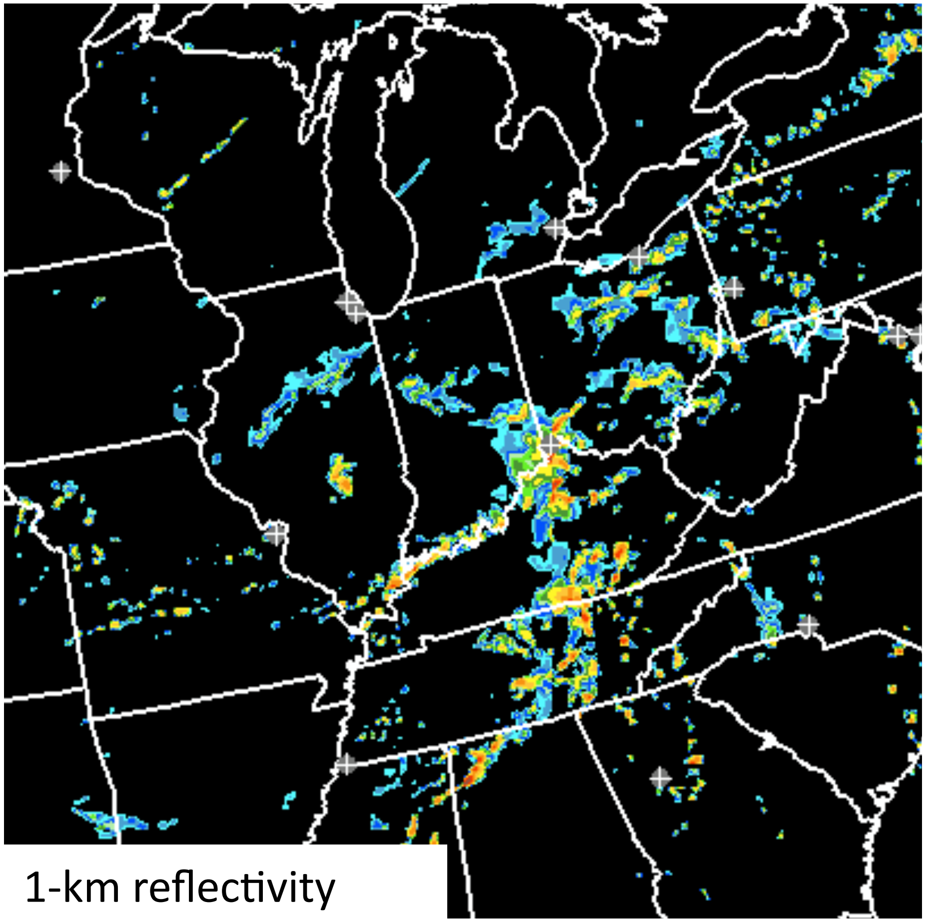
Initial Perturbations for HMT-10/11 "Cycling" GEFS (or SREF) perturbations



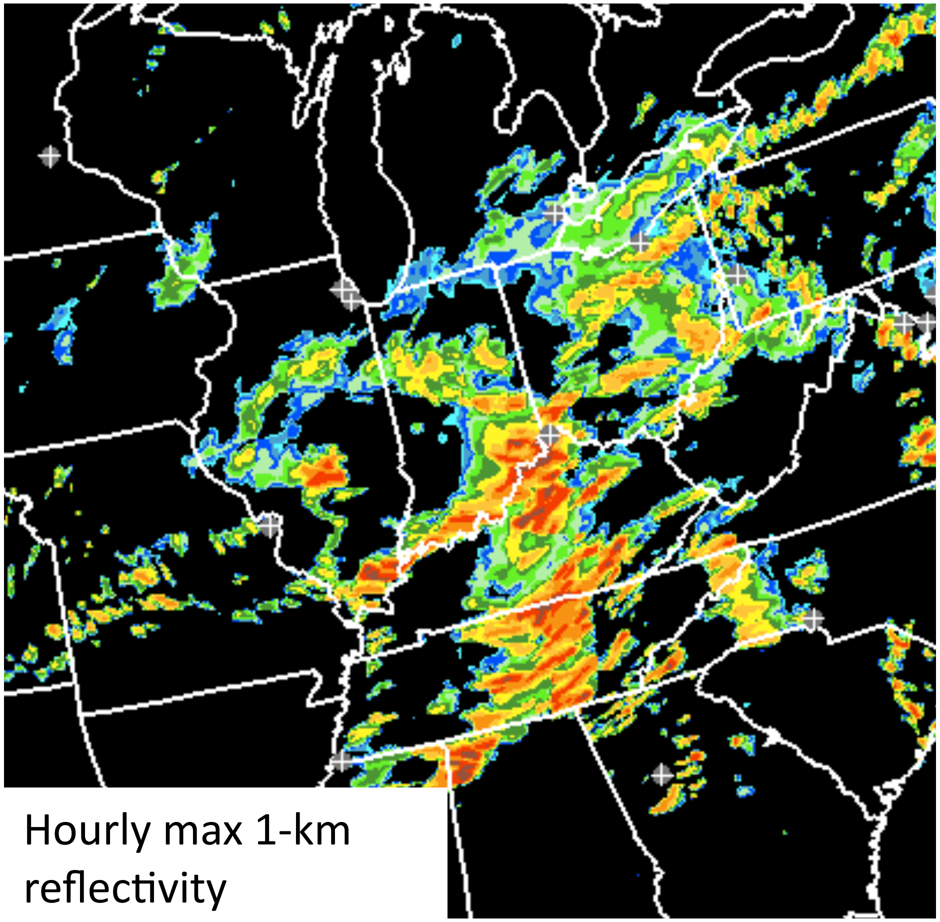
Optimizing the HCPF algorithm

Instantaneous reflectivity suffers from phase errors

Collecting the hourly maximum increases coverage, providing an excellent predictor



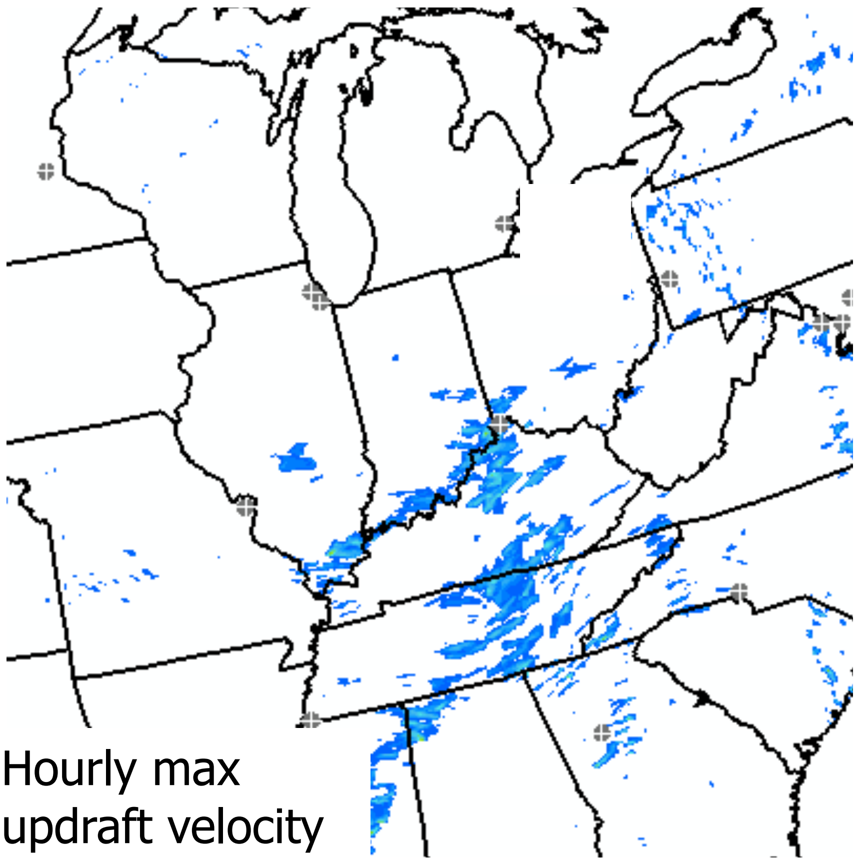
1-km reflectivity



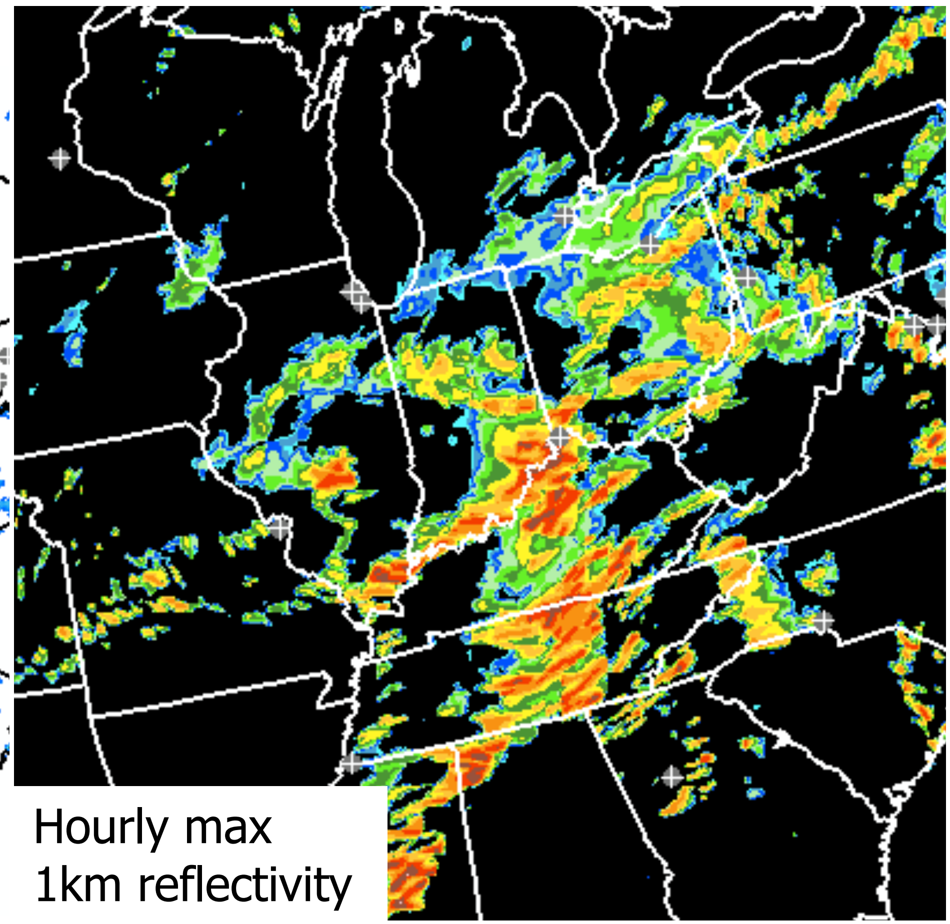
Hourly max 1-km reflectivity

Optimizing the HCPF algorithm

HRRR updraft velocity and reflectivity are strongly correlated, but the updraft field can more easily distinguish between convective and heavy stratiform precipitation



Hourly max updraft velocity

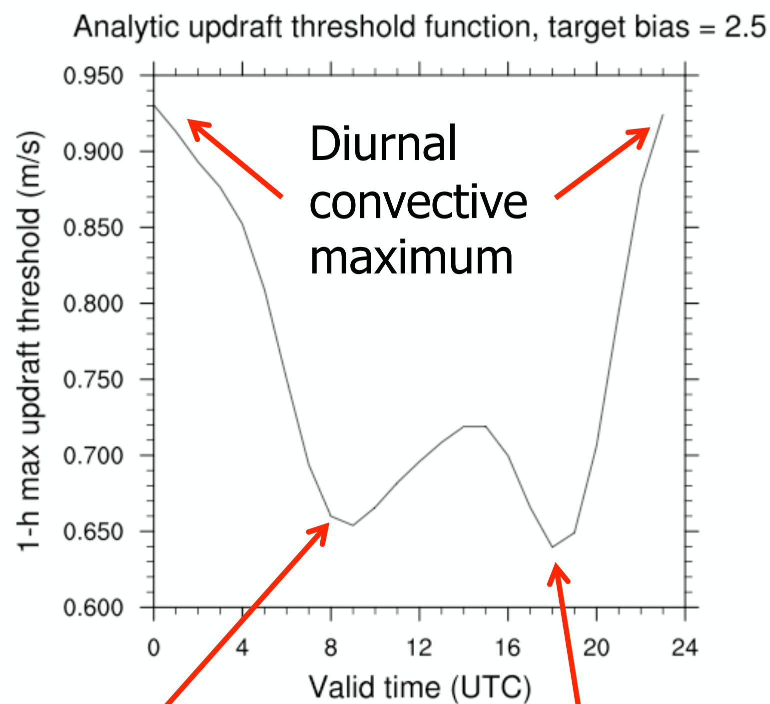


Hourly max 1km reflectivity

Optimizing the HCPF algorithm

Early versions of the HCPF had inconsistent skill, with large bias swings throughout the diurnal convective cycle

- Perform bias correction via a diurnally varying updraft (w) threshold
- Find threshold values at each hour that achieve a fixed bias
- Perform a Fourier synthesis to generate a smooth, analytic function for updraft velocity



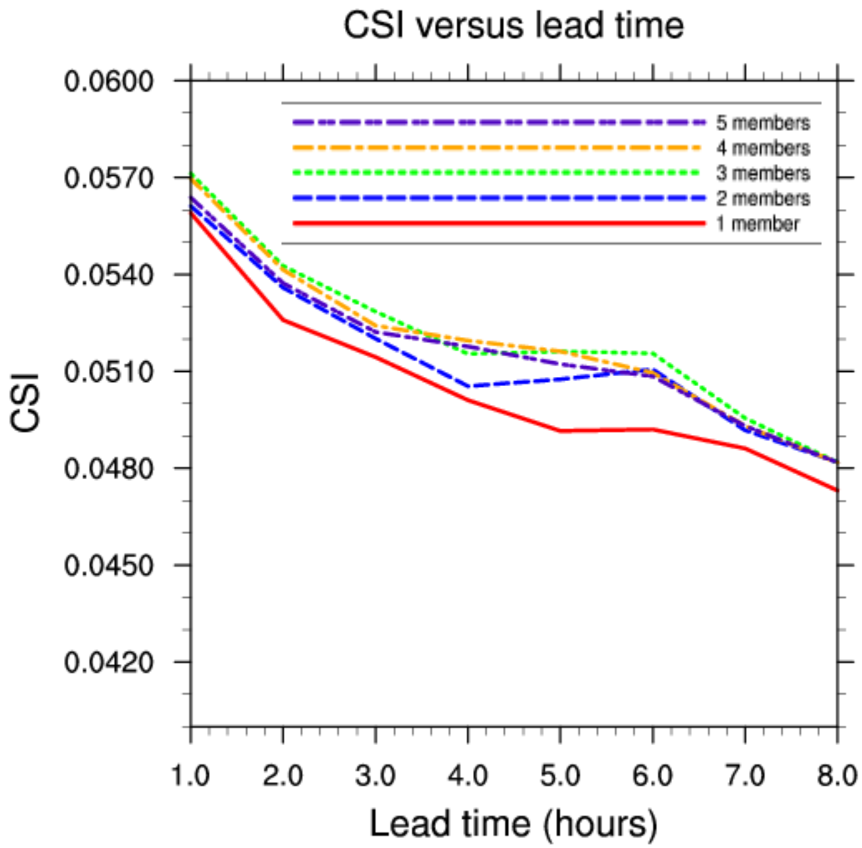
Diurnal convective minimum

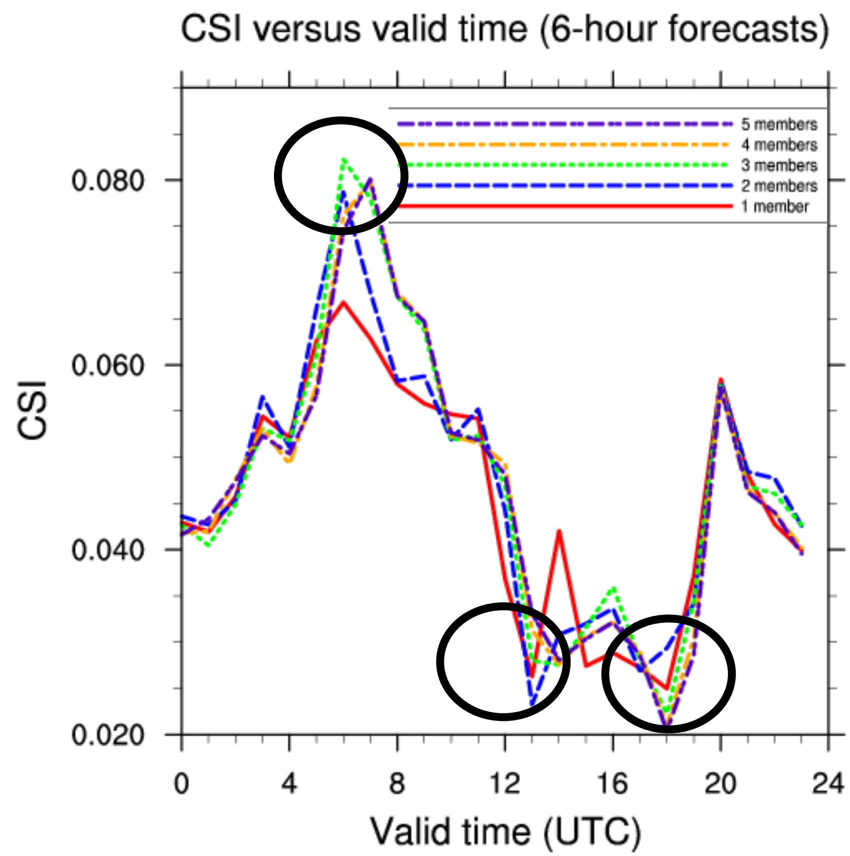
Convective initiation

HCPF probability verification

Verification period: August 2009, Comprising 540 ensemble forecasts

40% probability verified on a 4-km grid



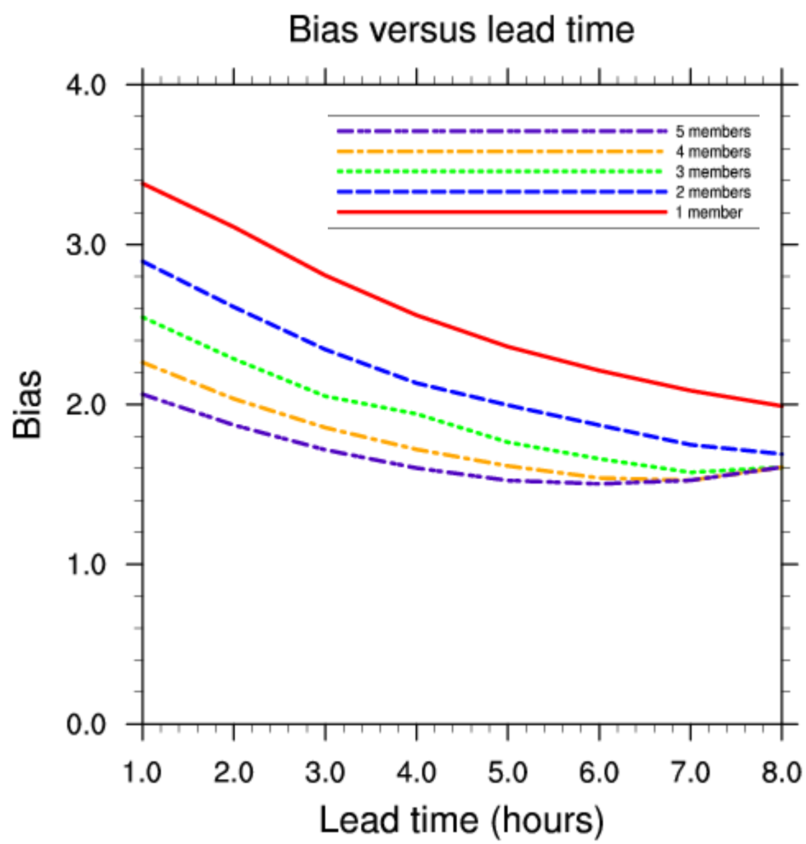


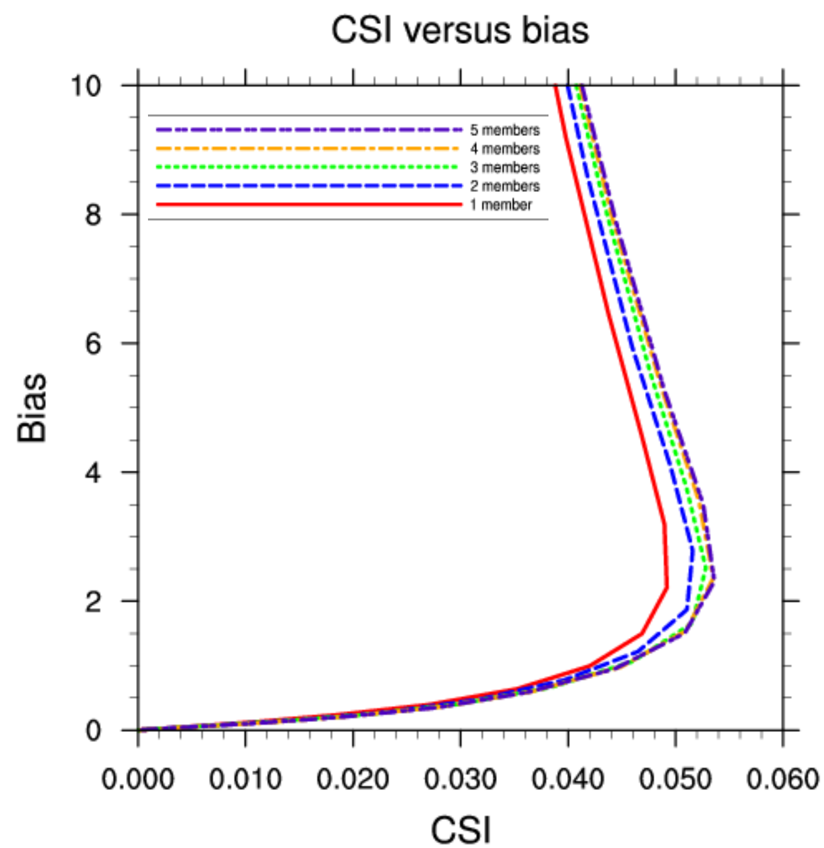
Highest overall skill (and largest gap between one and multiple members) occurs around 06 UTC when convection evolves upscale.

Double minima in skill: early morning hours, and midday convective initiation.

HCPF probability verification

40% probability verified on a 4-km grid





With more members, similar or slightly higher skill can be obtained, while substantially *reducing bias*.

Summary

- HRRR can provide an estimate of the likelihood (probability), timing, and location of convection through a time-lagged "ensemble-of-opportunity"

- HRRR convective probabilistic forecast (HCPF) shown to have comparable skill to other convective forecasts including the RUC convective probabilistic forecast (RCPF) and the Collaborative Convective Forecast Product (CCFP)

- Key challenge is under-forecasting moist convection (low bias/PoD) in weakly forced regions of convection (summer season) in early afternoon

- Improvements to HCPF under-forecast problem can be made through a variety of techniques including "time-smeared" forecasts, larger search radii, lower detection thresholds and limiting the ensemble to the more recent members

Where to go from here

• Incorporate deterministic forecast from recent member(s) to convey convective mode and complement probabilities to indicate likelihood

• Perform logistic regression to make probabilities statistically reliable while preserving sharpness/resolution to the forecasts

• Apply time-lagged ensemble to short-fuse forecast probabilities of other events such as high wind, hail, tornadoes, flash flooding, heavy ice/snow, fires

• Add additional ensemble members with different physics, initialized at same time, to improve HCPF which leads to…

• HRRR ensemble a.k.a. HRRRE in co-development between ESRL and National Centers for Environmental Prediction (NCEP) over the next 5 years