Ensemble Weather Forecasts

(a lecture in ATSC 507 - Num. Weather Prediction)

2023

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...with lots of help from
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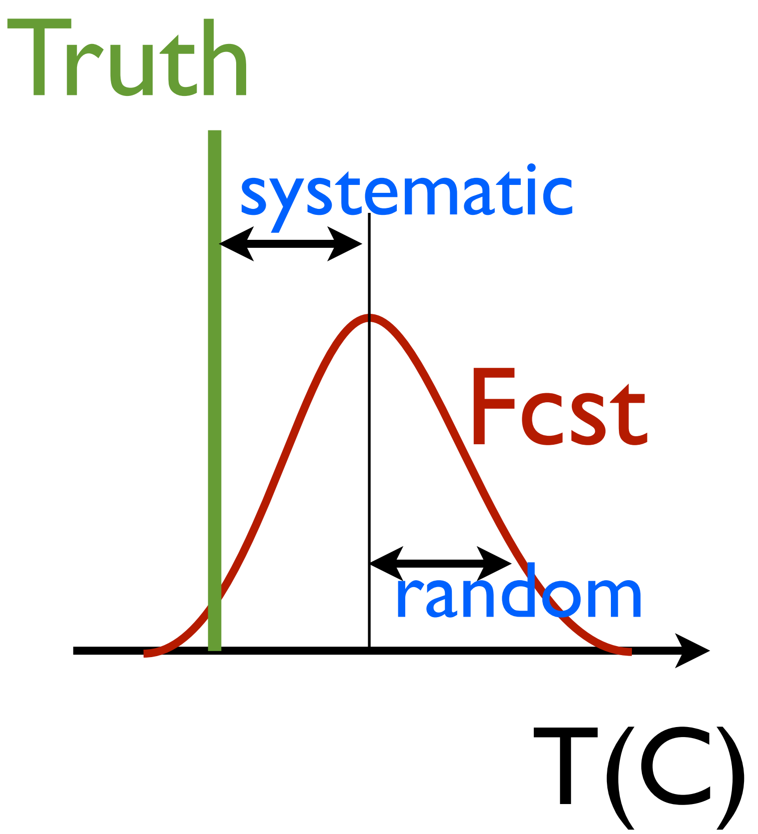
Henryk Modzelewski & Luca Delle Monache

Outline

- Role of ensembles in improving forecast skill.
- Operational ensemble forecast methods.
- Deterministic ensemble forecasts (DEF).
- Probabilistic forecasts from ensembles.
- Analog ensembles
- Ensemble-to-ensemble (E2E) models.
- Ways to display ensemble forecasts.

Ways to Correct Deterministic NWP Forecasts

- Systematic errors (bias) - remove with statistical post-processing (e.g., regression, neural networks, genetic programming...)

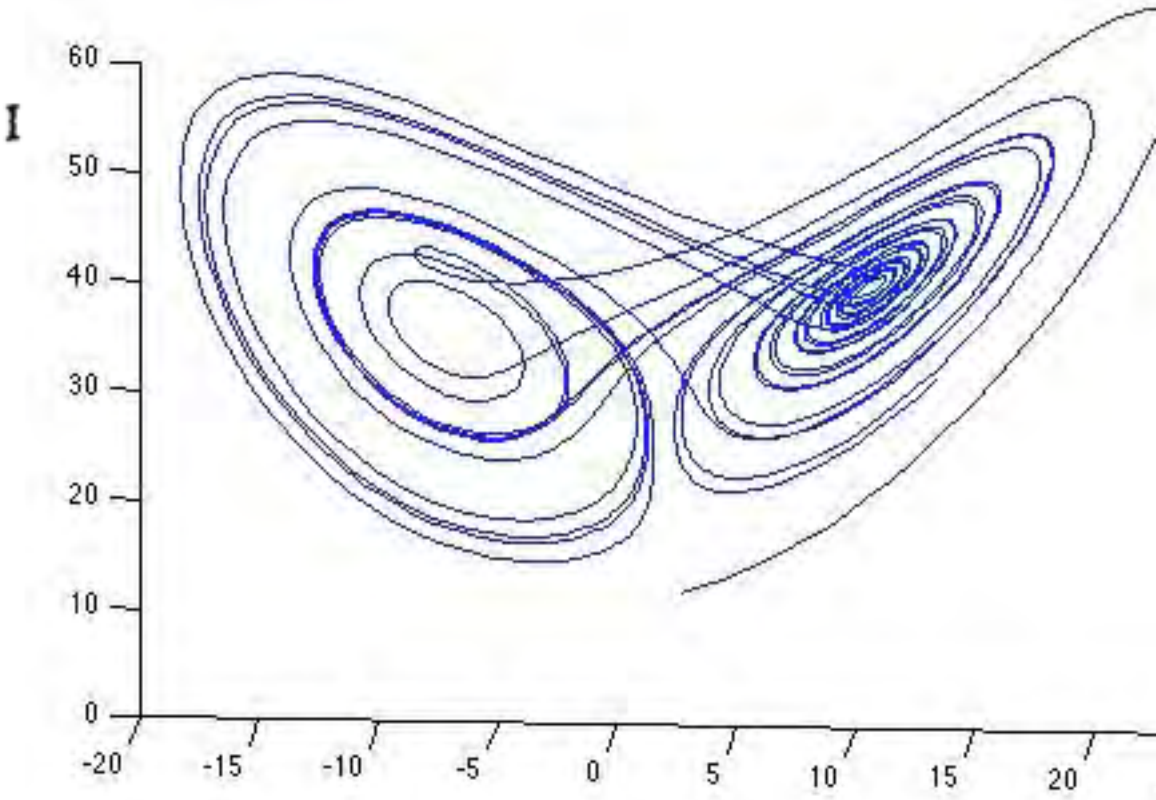


- Random errors (non-linear dynamics/chaos) - reduce by combining an ensemble of many weather forecasts into an ensemble average.

- Procedure - ALWAYS remove the biases from the individual runs BEFORE you combine them into an ensemble.

Lorenz & the Birth of Chaos Theory (1963)

JOURNAL OF THE ATMOSPHERIC SCI



homepages.math.uic.edu

Deterministic Nonperiodic Flow[1]

EDWARD N. LORENZ

Massachusetts Institute of Technology

(Manuscript received 18 November 1962, in revised form 7 January 1963)

ABSTRACT

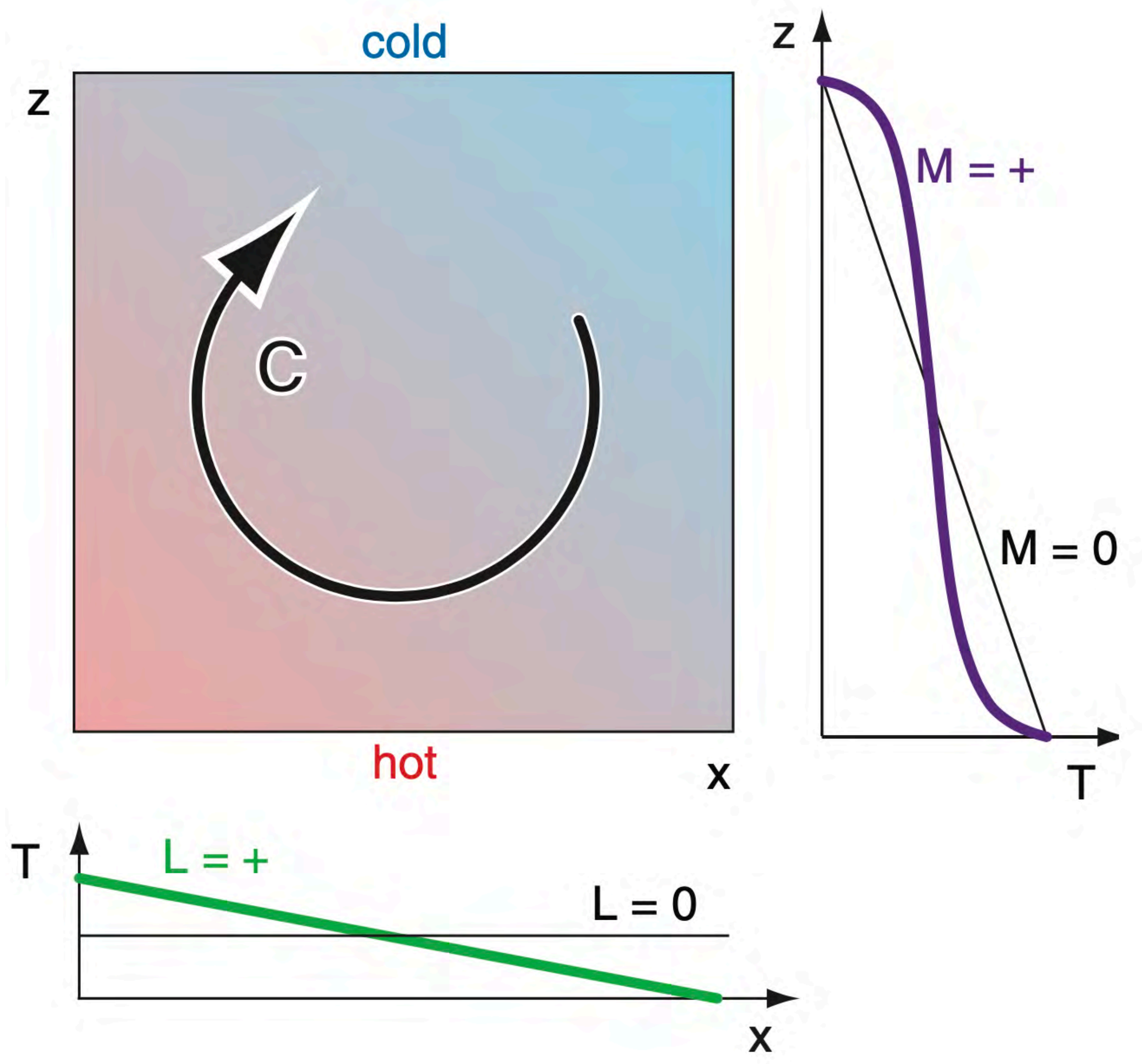
Finite systems of deterministic ordinary nonlinear differential equations may be designed to represent forced dissipative hydrodynamic flow. Solutions of these equations can be identified with trajectories in phase space. For those systems with bounded solutions, it is found that nonperiodic solutions are ordinarily unstable with respect to small modifications, so that slightly differing initial states can evolve into considerably different states. Systems with bounded solutions are shown to possess bounded numerical solutions.

A simple system representing cellular convection is solved numerically. All of the solutions are found to be unstable, and almost all of them are nonperiodic.

The feasibility of very-long-range weather prediction is examined in the light of these results.

Lorenz & the Birth of Chaos Theory (1963)

Picture a simpler nonlinear system (convection in a tank), with significantly fewer degrees of freedom compared to the real atmosphere.



$$\frac{\partial C}{\partial t} = \sigma \cdot (L - C)$$

$$\frac{\partial L}{\partial t} = r \cdot C - L - C \cdot M$$

$$\frac{\partial M}{\partial t} = C \cdot L - b \cdot M$$

Stull, 2017

Sensitive dependence to initial conditions

made with parameter values:

$\sigma = 10.0,\ b = 8/3,$ and $r = 28$

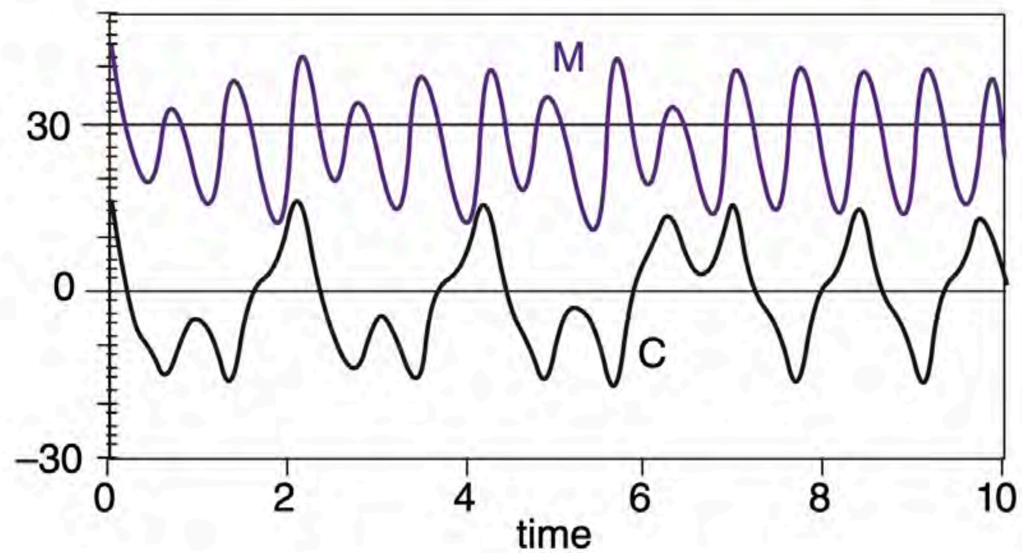
and initial conditions:

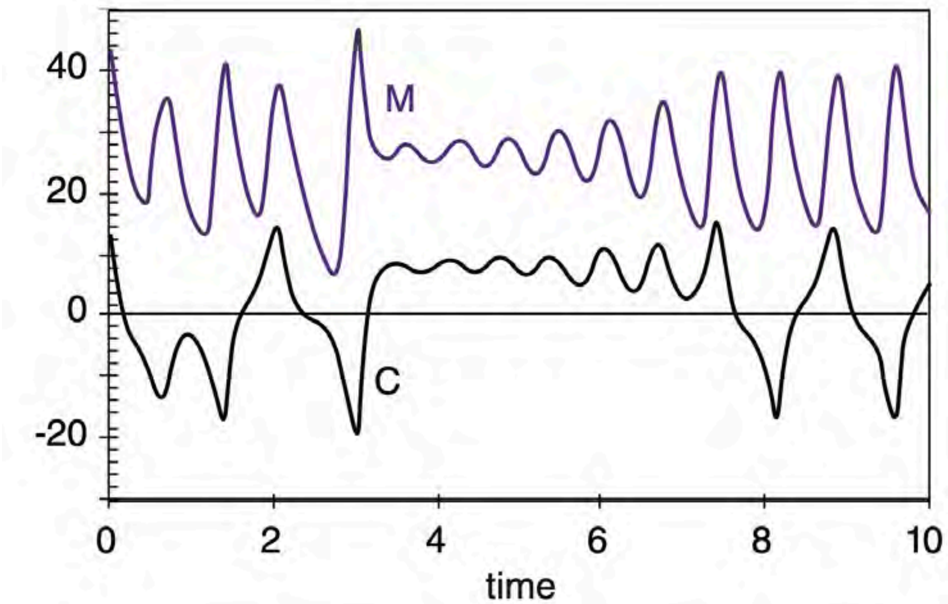
$C(0) = 13.0,\ L(0) = 8.1,$ and $M(0) = 45.$

Given: $C(0) = 13.0,\ L(0) = 8.1,$ and $M(0) = 44,$
and $\sigma = 10.0,\ b = 8/3,\ r = 28.$
Find: $C(t) = ?,\ L(t) = ?,\ M(t) = ?$

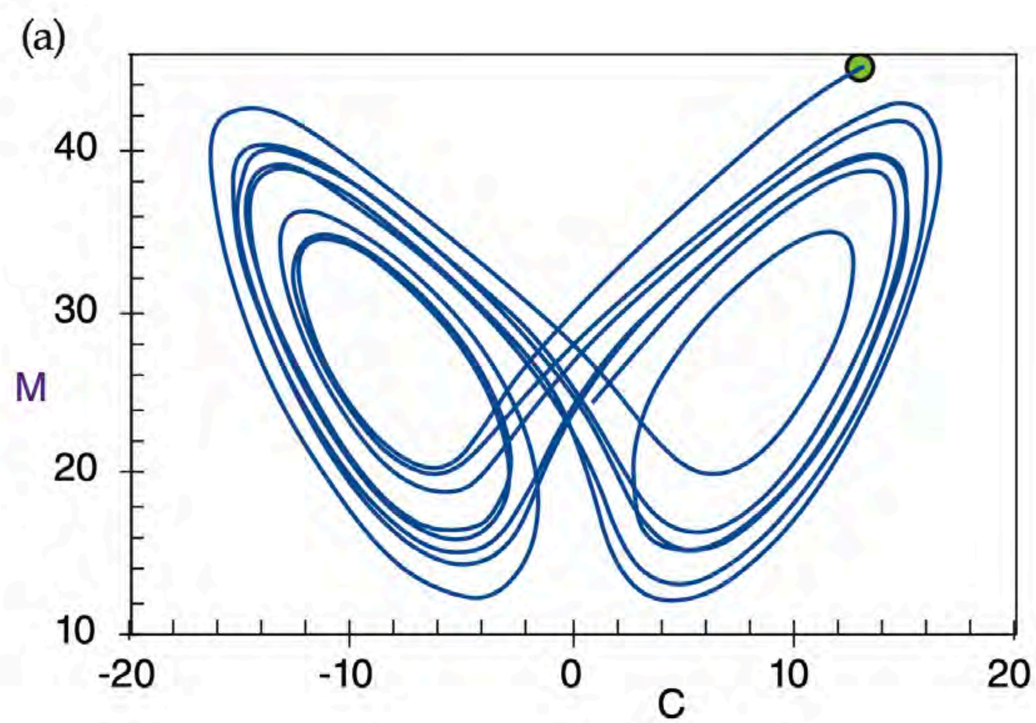
As in the previous Sample Application.

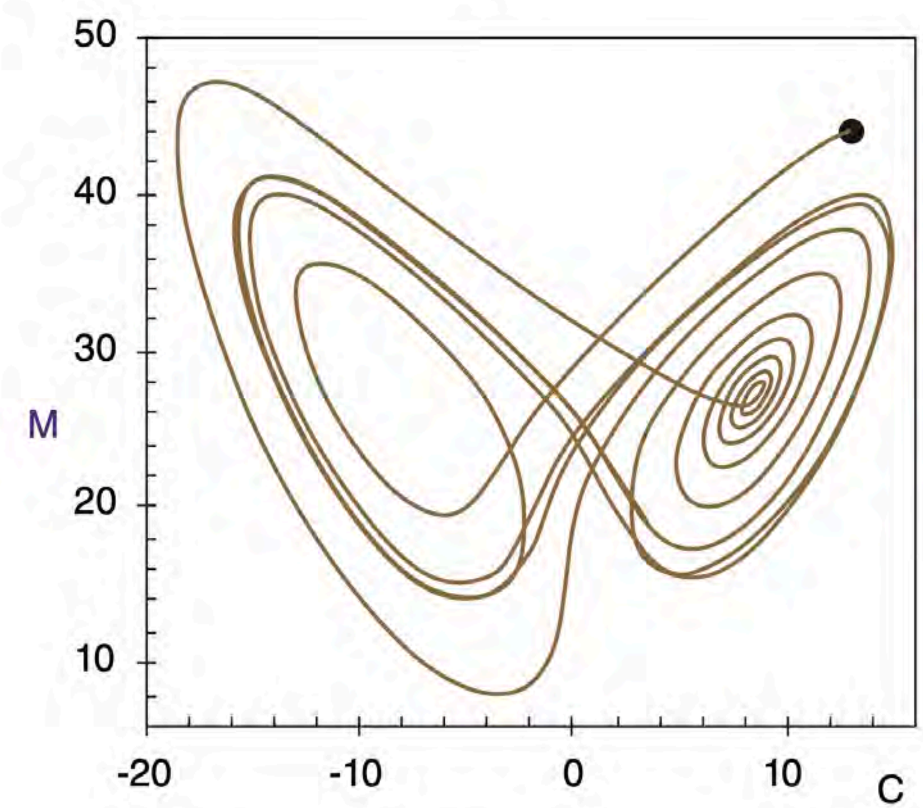
Time series





Phase space



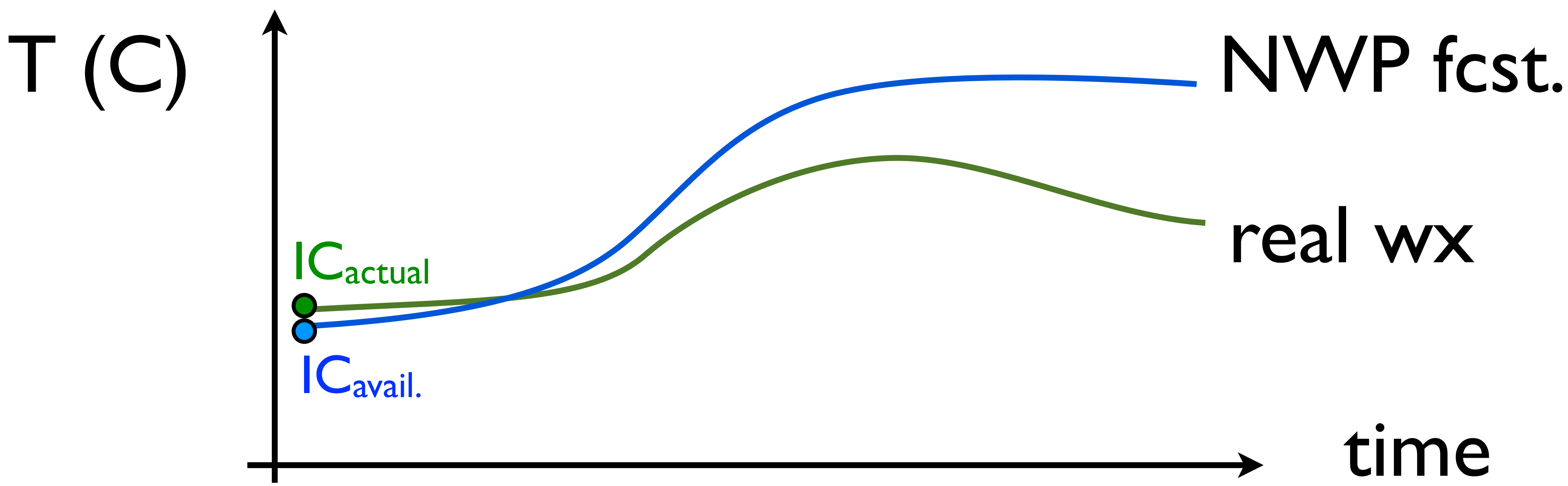


Stull, 2017

Sensitive Dependence on Initial Conditions

If we (NWP modelers) have done a good job having our model approximate the real physics,
then the model should have the same sensitivities as the real atmosphere.

Thus, a slight difference in initial conditions between the model and the atmos might cause an increasing error as the forecast progresses.



Sensitive Dependence on Initial Conditions

- Defines the limits of weather predictability (Unless you make a new discovery.)
- Even if NWP model was a perfect description of the weather, then if the model starts with a slightly different initial condition than the real weather, then the forecast diverges from truth

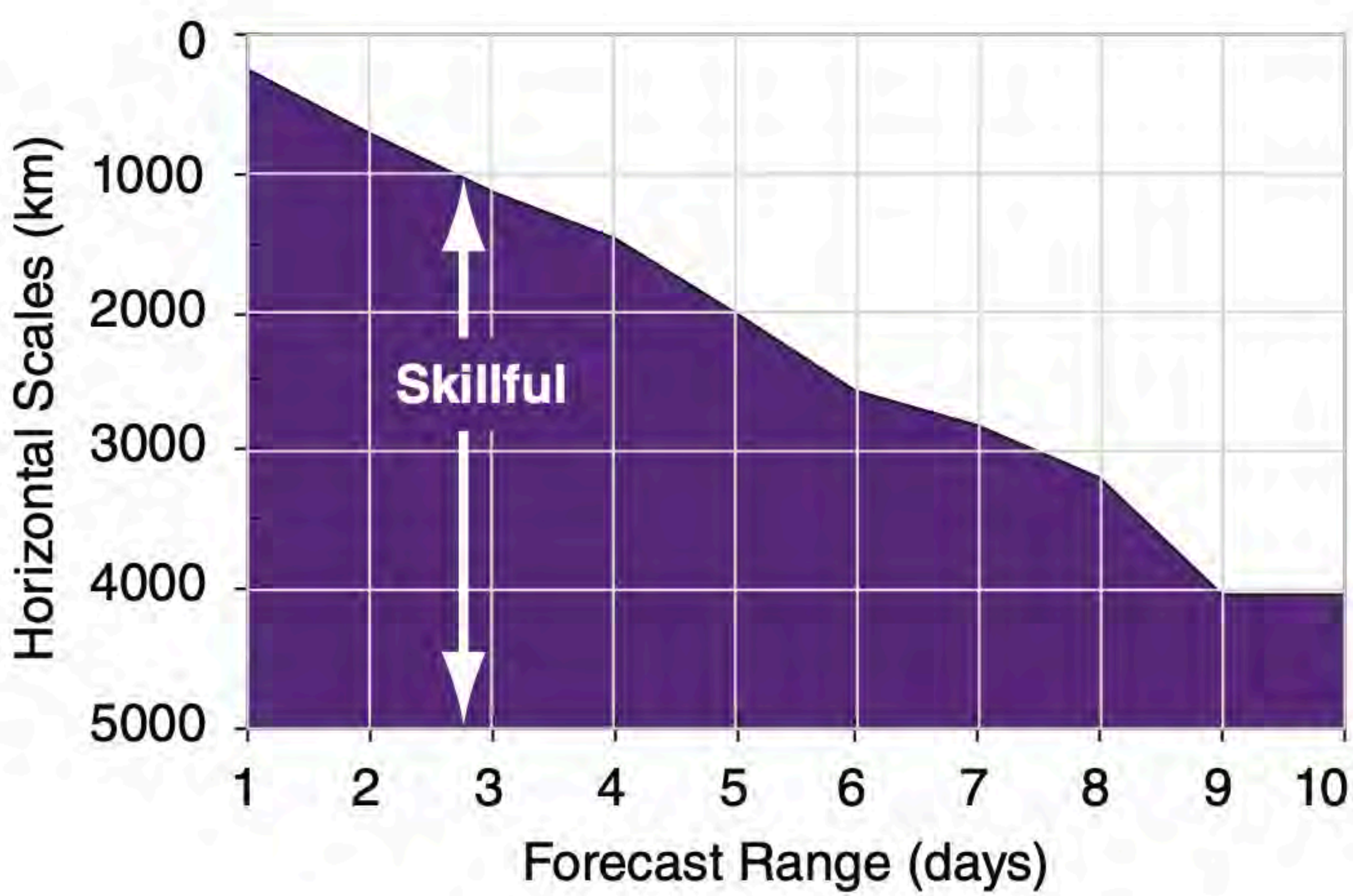


Figure 20.14
Range of horizontal scales having reasonable forecast skill (shaded) for various forecast durations. [from the European Centre for Medium Range Weather Forecasts (ECMWF), 1999]

Initialization (Data Assimilation) is Critically Important for Accurate Weather Forecasts

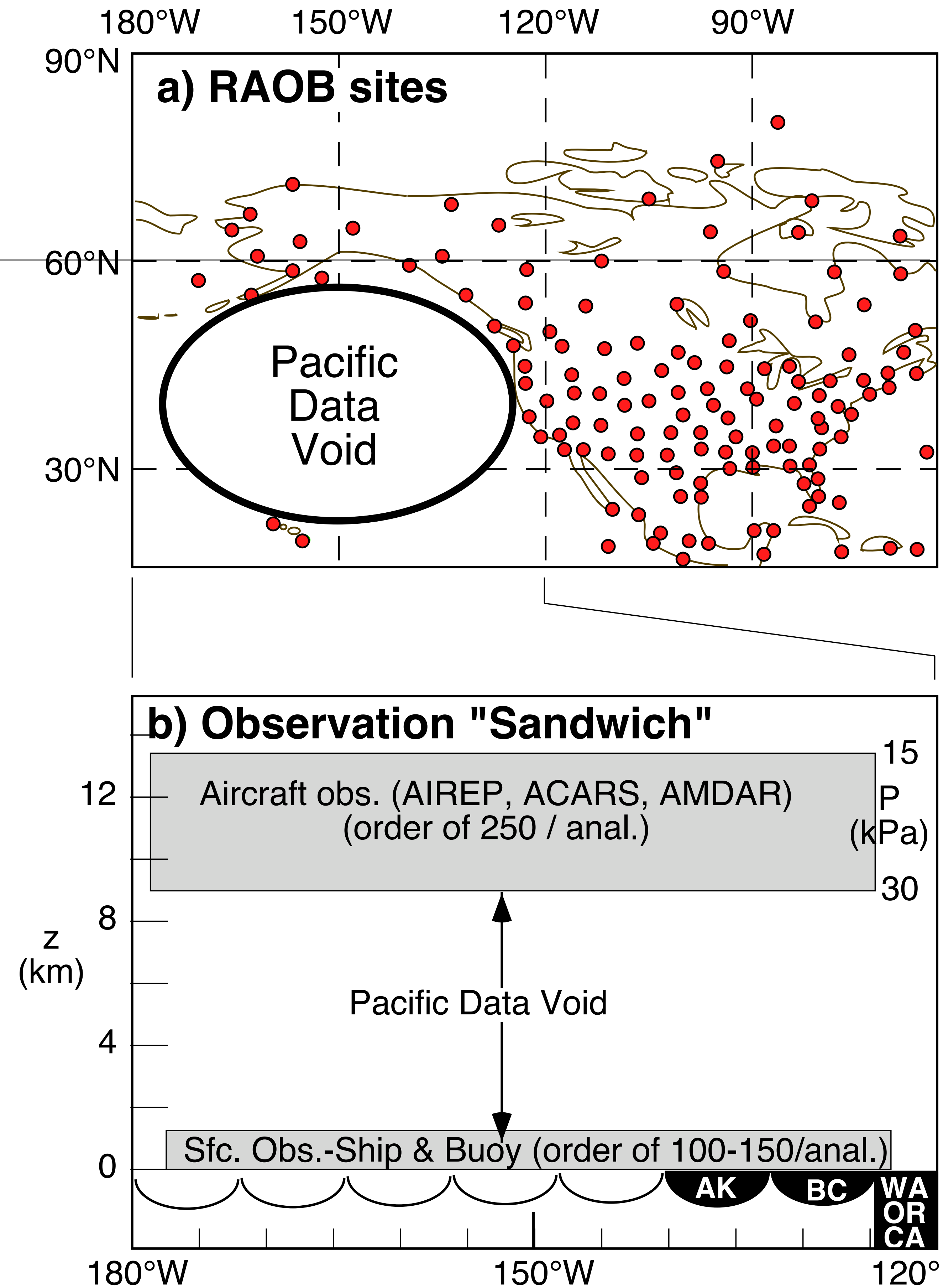
Data Assimilation is where weather observations (truth but with errors; only at irregularly spaced station locations) is merged with a first guess NWP (previous forecast, in a regular grid, reduced skill) to create an "Analysis", which is the IC for the forecast.

- At the most successful forecast centers (e.g., ECMWF), more computer time is spent on data assimilation than on the actual forecast.
- Three-dimensional (3DVar) and four-dimensional (4DVar) variational data assimilation are very important.
- Stull's team doesn't have the computer power to do data assimilation every day. So we import our ICs from big government centers.

As McCollor mentioned:

Need to Fill the Pacific Data Void

- Paucity of upstream in-situ data over the Pacific causes errors in the **initial conditions** of NWP.
- This is currently the weakest link in making more accurate NWP forecasts for W. Canada, because of the sensitive dependence of fcsts on initial conditions.



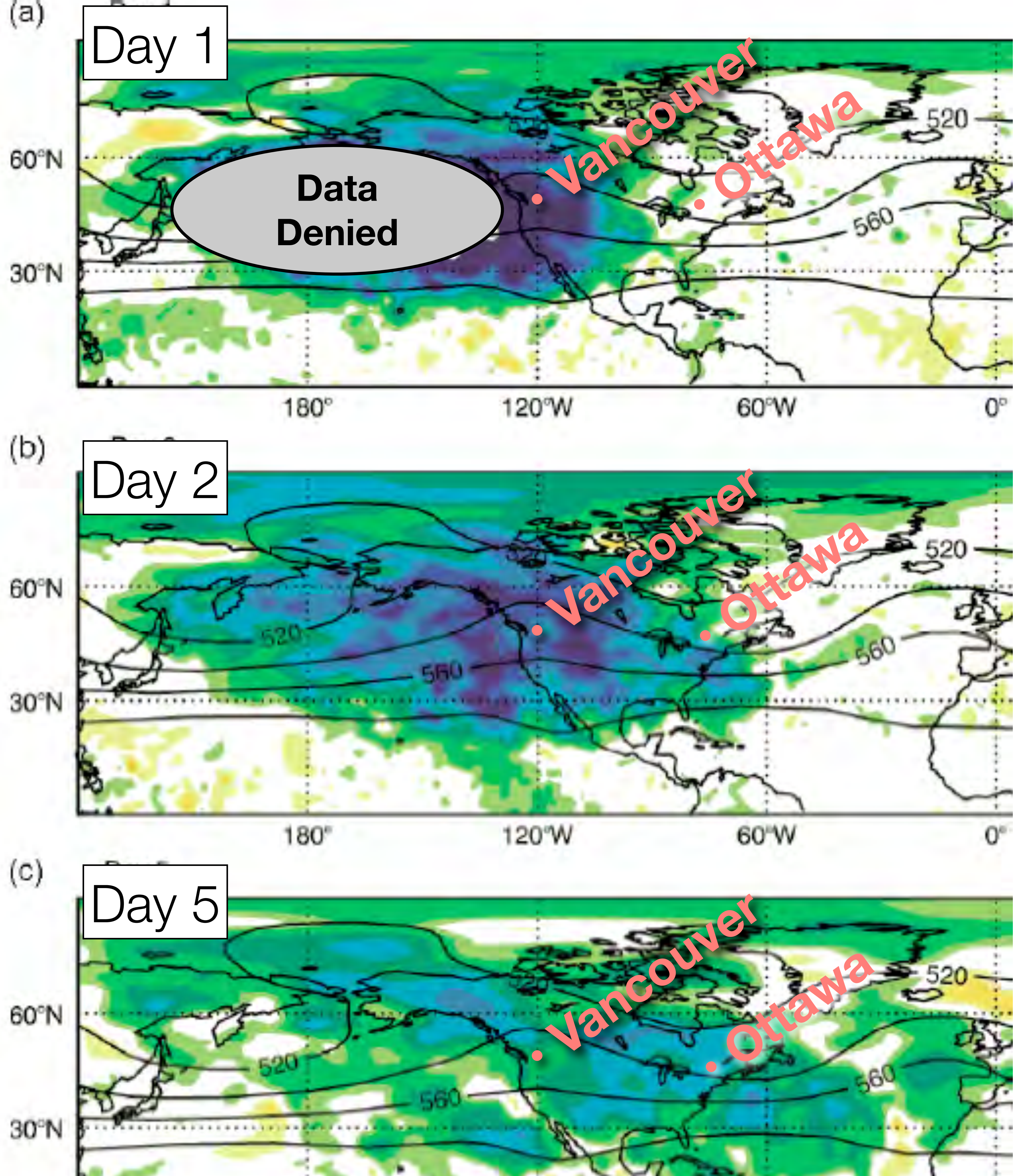
Data Denial Experiment

Kelly et al, 2007, QJRMS

Relative RMS errors in the 50 kPa geopotential heights, when all observations over the Pacific are excluded from the ECMWF data assimilation for Day 0, vs. those normally retained by ECMWF.

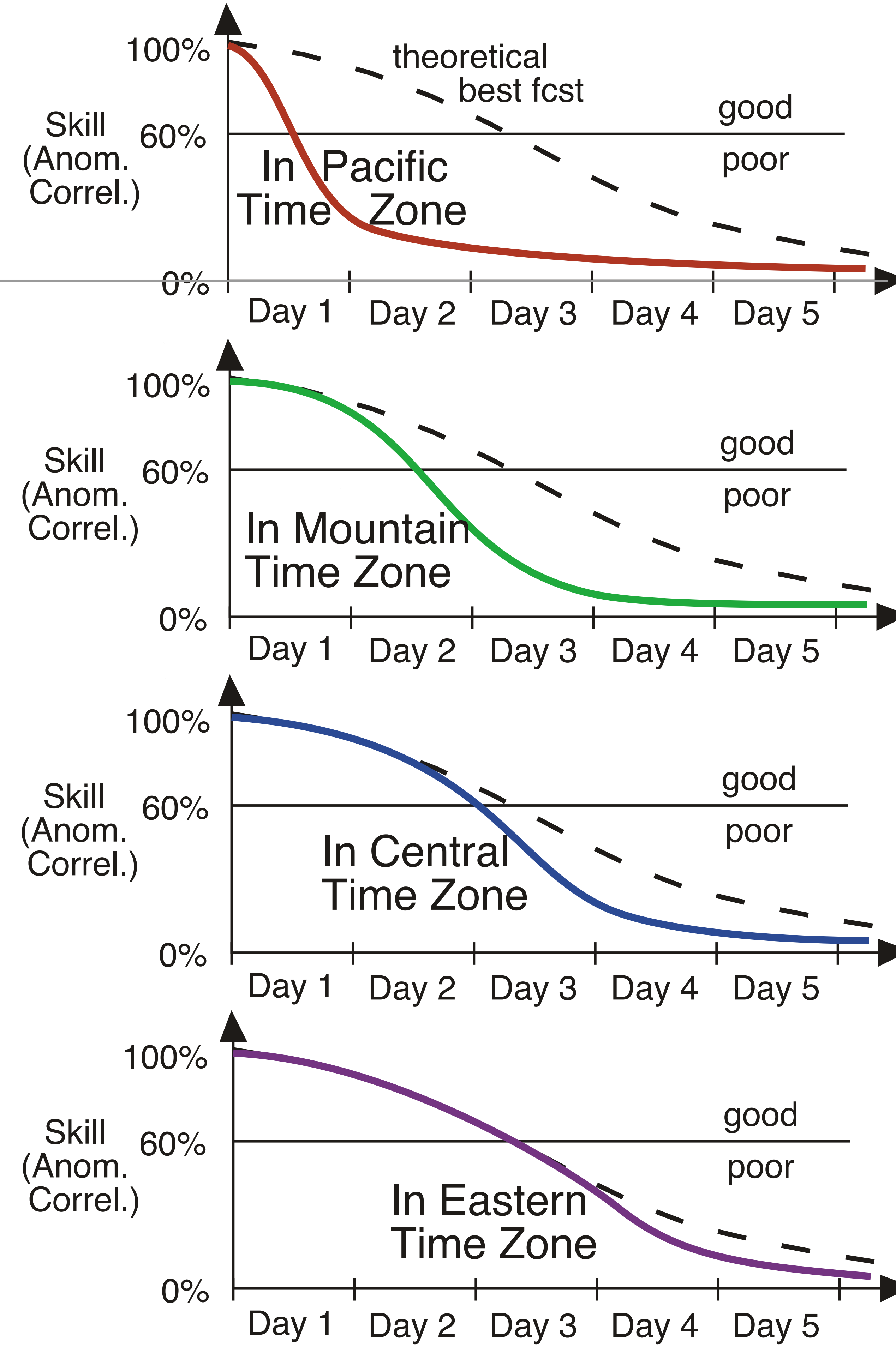
Green, **blue**, **dark purple** show worse forecasts,

while **yellow** and **red** show positive impact.



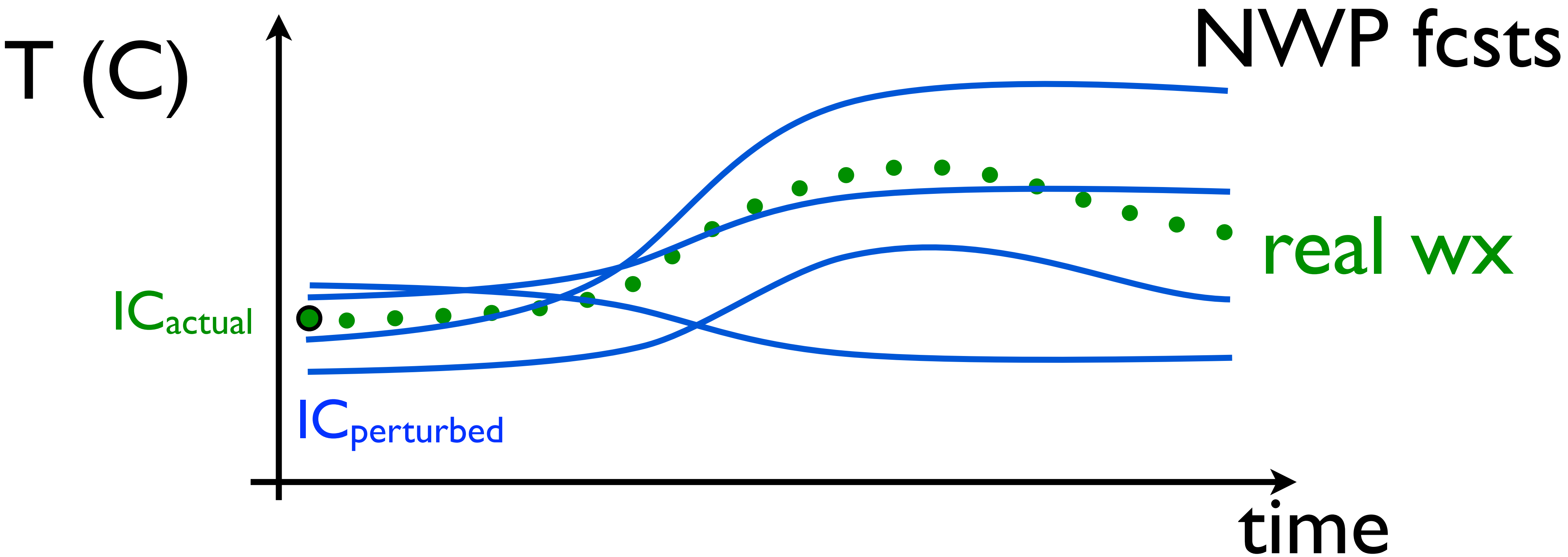
Forecasts are Less Accurate in W. Can. because of Bad ICs Upstream

- The potential economic loss in different regions of Canada is proportional to the area between the solid curve and the dashed line.
- W. Canada has the largest losses, starting at shorter range forecasts.



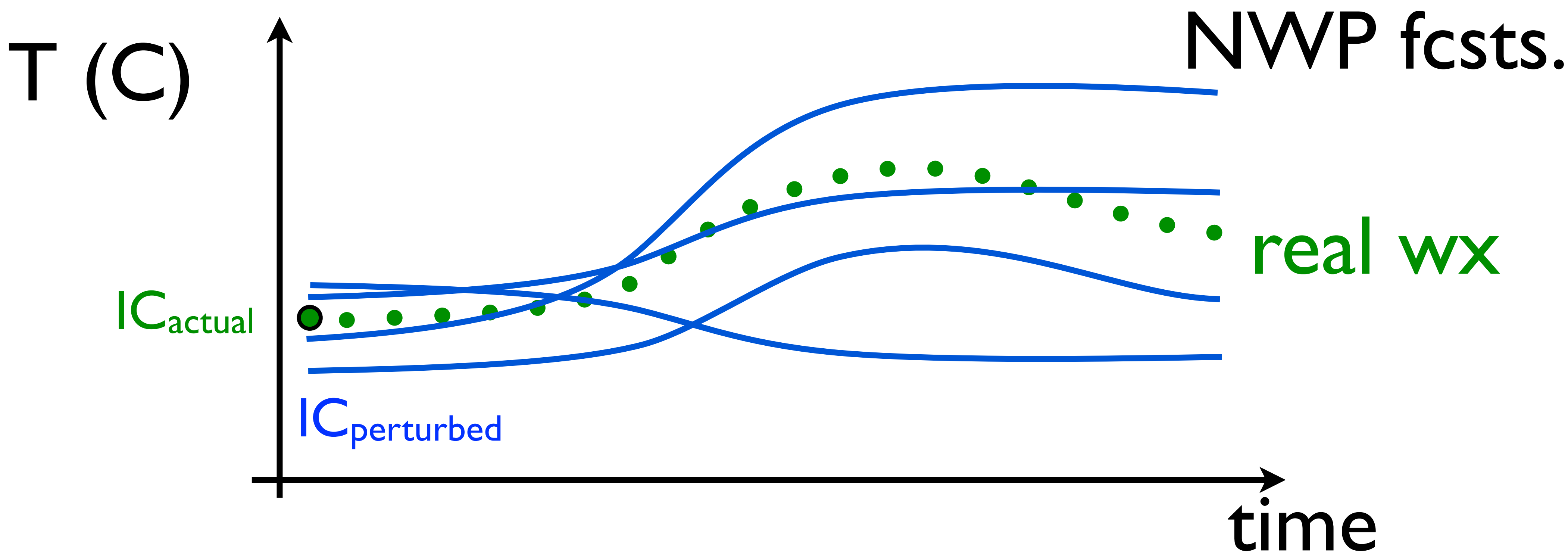
The Problem gives the Solution

- Intentionally start with many slightly wrong initial conditions (ICs), and use the spread of the resulting forecasts to hopefully “bracket” the true weather.

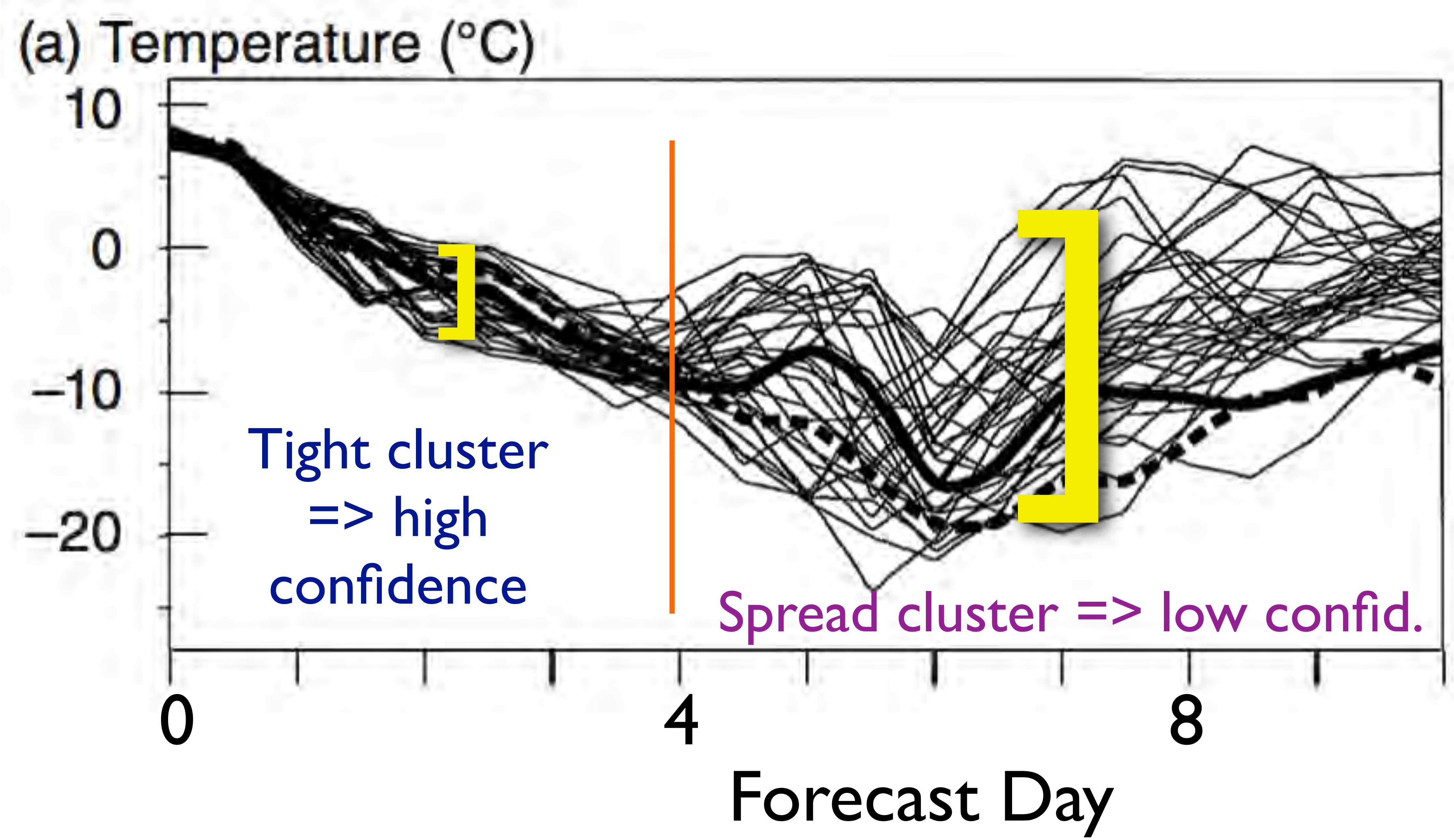


Ensemble Mean & Spread

- The average of the ensemble forecasts is the best "deterministic" forecast (i.e., better than any individual run when averaged over many days of fcsts.
- The spread indicates the (a) uncertainty or skill, & (b) the probability of alternate outcomes.

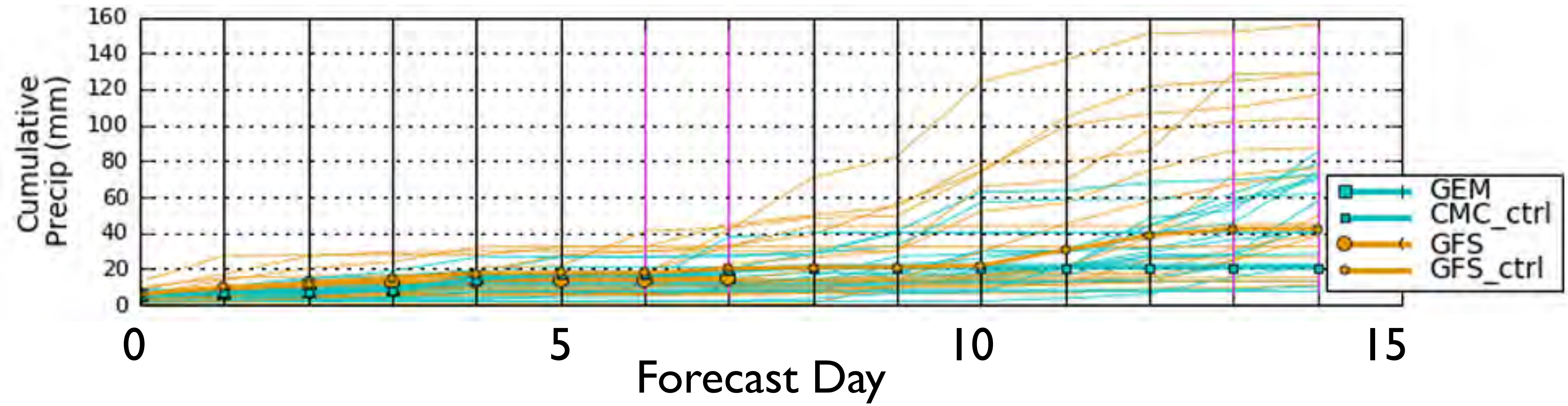


Sample from ECMWF

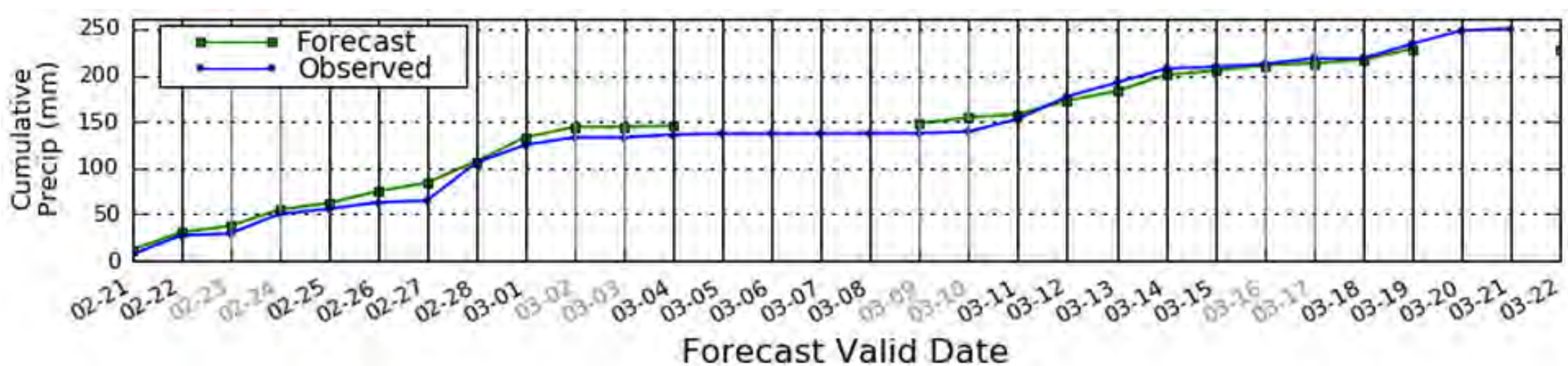


Sample from: North American Ensemble Fcst System (NAEFS)

for Wolf River stn., as modified at UBC

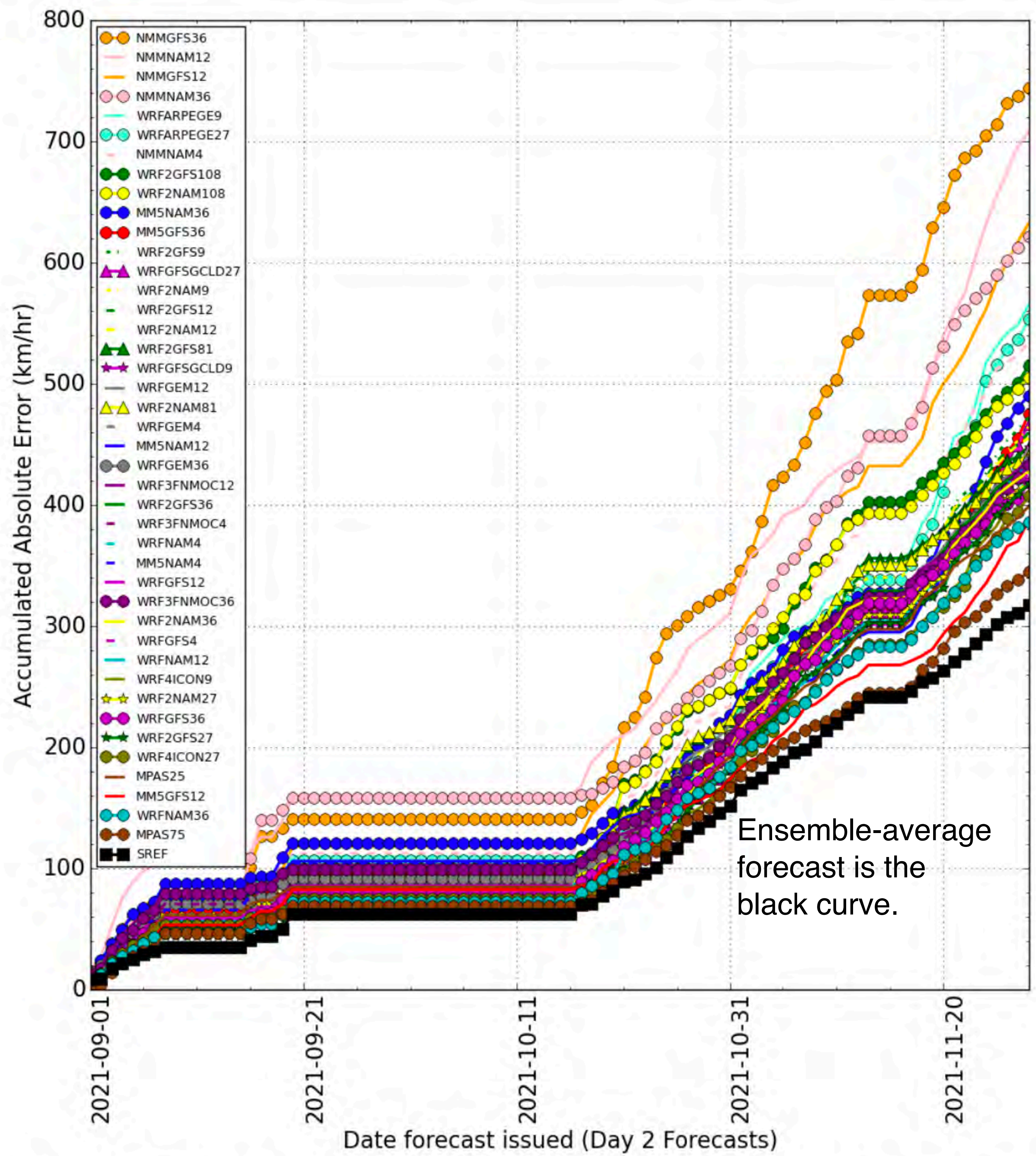


Verification of ensemble over past month at Wolf Riv.



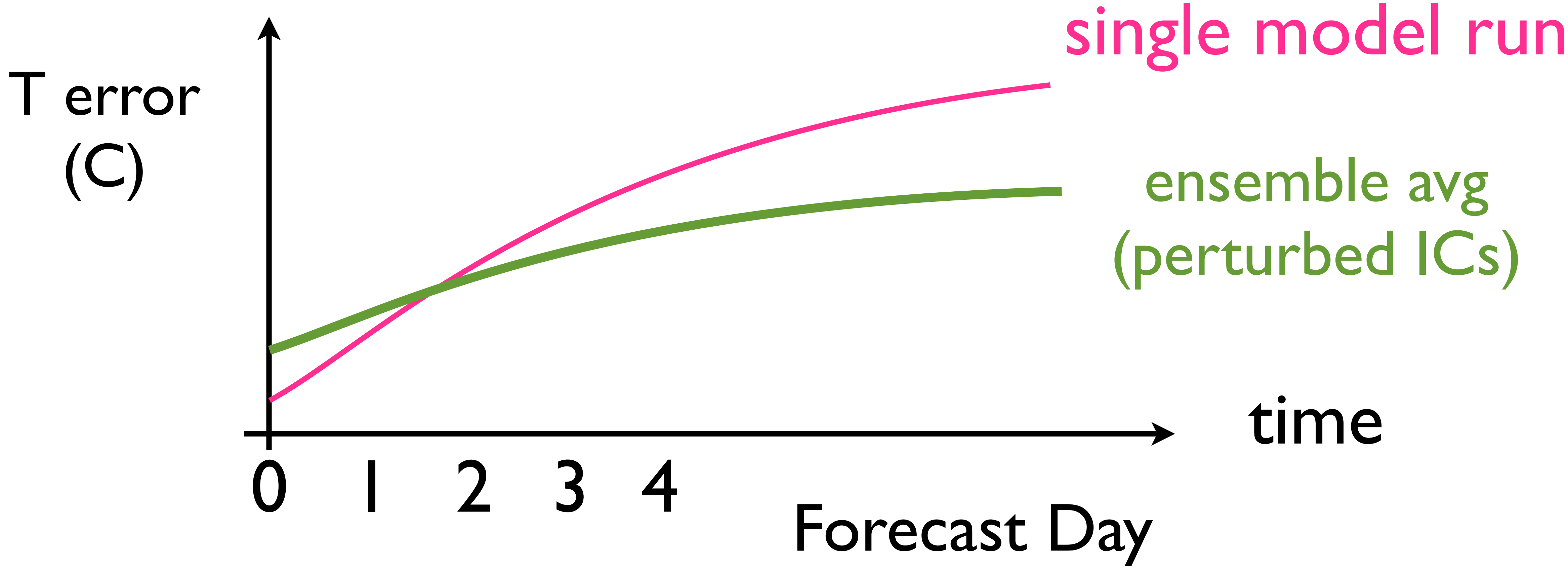
Sample from: UBC ensemble forecasts

of hub-height wind speed at a wind farm in BC



Accumulated Absolute Error for Day 2 forecast for each individual SREF ensemble member from the start of the season. Less is better.

Error Growth



- For IC perturbations, ensemble average gives worse forecast for first 1 to 2 days. Thus NOT useful for short-range forecasting. This is not a problem in central & eastern Canada, which has good short-range forecasts even from single deterministic NWP models, because they are less affected by the Pacific data void.

- Sadly, for western Canada, even the short-range forecasts are relatively poor, and are not helped by ensemble forecasting from perturbed ICs.

- Instead, at UBC, we use multiple model cores, physics, grid sizes, and ICs from different gov't centers.

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Many ways to perturb a reference fcst to generate ensembles

1. ICs
2. BCs (for limited-area model)
3. physics
4. numerics
5. grid resolutions
6. lagged in time
7. models (= multi-model ensemble)
8. terrain
9. compilers & compiler optimizations

At UBC, we use (1), (2), (5), (7) for Short-range Ensemble Fcsts (SREF)

History of Operational Ensembles

- 1988 - UK Met. Office (UKMO)
- 1992 - ECMWF - multi-IC (singular vectors)
- 1992 - NCEP - multi-IC (bred vectors)
- 1996 - UBC - multi-model, multi-resolution
- 1996 - CMC - multi-IC (via data assim; perturbed obs.)
- 2004 - CMC & NCEP & NMSM => NAEFS (super-ensemble)

NAEFS Current Configuration

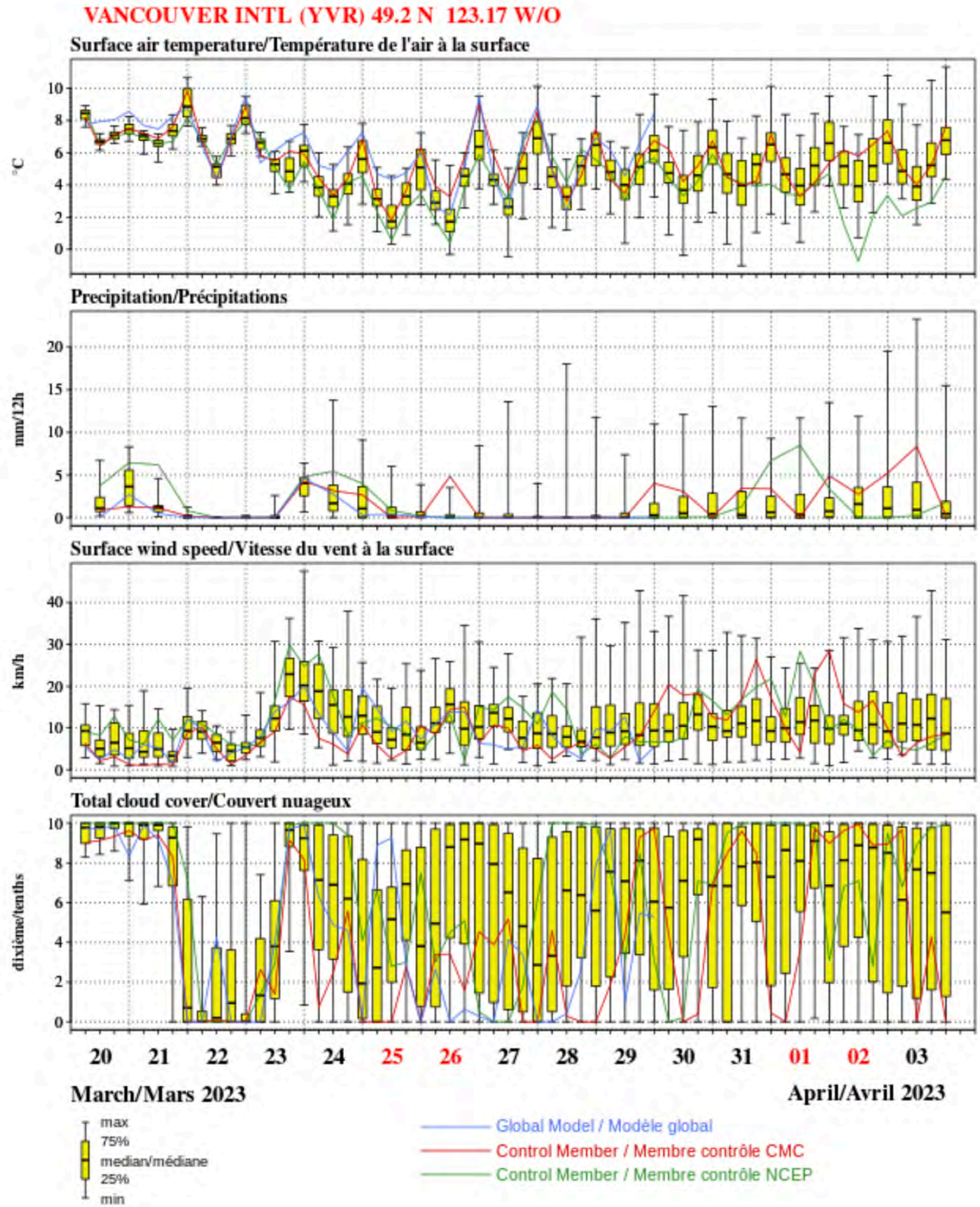
Updated: February 23rd 2010

	NCEP	CMC
Model	GFS	GEM
Initial uncertainty	ETR	EnKF
Model uncertainty/Stochastic	Yes (Stochastic Pert)	Yes (multi-physics)
Tropical storm	Relocation	None
Daily frequency	00,06,12 and 18UTC	00 and 12UTC
Resolution	T190L28 (d0-d16)~70km	(d0-d16) ~1.0degree
Control	Yes	Yes
Ensemble members	20 for each cycle	20 for each cycle
Forecast length	16 days (384 hours)	16 days (384 hours)
Post-process	Bias correction (same bias for all members)	Bias correction for each member
Last implementation	February 23rd 2010	July 10th 2007

Example of a NAEFS forecast

In general, ensembles with more "good" members creates a better ensemble average, because ...
(class discussion here)

Another version of NAEFS includes an additional model: FNMOC, and it was shown to verify better.



Weather Forecast Research Team, UBC

We make <u>operational</u>, daily ensemble forecasts using multi models, multi initial & boundary conditions, and multi resolutions.

http://weather.eos.ubc.ca/wxfcst/

Tailored Weather Forecasts for
UBC - Weather Forecast Research Team (Internal)

[UBC EOSM Rooftop] [UBC ESB Rooftop - 2 day forecast] [UBC ESB Rooftop - 7 day forecast]
[Whistler Village - 2 day forecast] [Whistler Village - 7 day forecast]
[BC Hydro Edmonds Heliport - 2 day forecast] [BC Hydro Edmonds Heliport - 7 day forecast]
[Whitehorse Airport] [Yellowknife Airport]
[Arctic forecast]

Your current choice of the initialization time on our Web Pages is 00 UTC

00Z 06Z 12Z 18Z

Model:	MM5	MM5	WRF (ARW)	WRF (ARW)	WRF (ARW)	WRF (ARW)	WRF (ARW) GC01	WRF (ARW) ARPEGE	WRF (ARW) BSky	WRF (ARW) ICON	WRF (ARW) RDPS	WRF (NMM)	WRF (NMM)	WRF (ARW)	WRF (ARW)	WRF (ARW)	WRF (ARW)	MPAS25	Ensemble
Init. Cond.:	NAM	GFS	GEM	NAM	GFS	FNMOC	GFS	ARPEGE	NAM	ICON	RDPS	NAM	GFS	NAM	GFS	NAM	GFS	GFS	N/A
Init. Time (UTC):	00	00	00	00	00	00	00	00	00	00	00	00	00	00	00	00	00	00	00
Extra Large	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	3.5 days [108 km]	7.5 days [108 km]	3.5 days [81 km]	7.5 days [81 km]	5.0 days [92 km]	N/A
Large	2.5 days [36 km]	3.5 days [36 km]	7 days [36 km]	3.5 days [36 km]	7.5 days [36 km]	5.0 days [36 km]	7.5 days [27 km]	4.25 days [27 km]	3.5 days [36 km]	7.5 days [27 km]	N/A	3.5 days [36 km]	7.5 days [36 km]	3.5 days [36 km]	7.5 days [36 km]	3.5 days [27 km]	7.5 days [27 km]	5.0 days [25 km]	N/A
Medium	2.5 days [12 km]	3.5 days [12 km]	7 days [12 km]	3.5 days [12 km]	7.5 days [12 km]	5.0 days [12 km]	7.5 days [9 km]	4.25 days [9 km]	3.5 days [12 km]	7.5 days [9 km]	3.5 days [9 km]	3.5 days [12 km]	7.5 days [12 km]	3.5 days [12 km]	7.5 days [12 km]	3.5 days [9 km]	7.5 days [9 km]	N/A	N/A
Small	2.5 days [4 km]	3.5 days [4 km]	3.5 days [4 km]	2.5 days [4 km]	3.5 days [4 km]	3.5 days [4 km]	N/A	N/A	2.5 days [4 km]	N/A	3.5 days [3 km]	3.5 days [4 km]	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Extra Small	N/A	3.5 days [1.3 km]	N/A	N/A	3.5 days [1.3 km]	N/A	N/A	N/A	N/A	N/A	2.5 days [1 km]	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Points:																			
Profiles	Open	Open	Open	Open	Open	Open	Open	Open	Open	Open	Open	Open	Open	Open	Open	Open	Open	Open	Open
Meteograms	Open	Open	Open	Open	Open	Open	Open	Open	Open	Open	Open	Open	Open	Open	Open	Open	Open	Open	Open

Your current choice of the time zone display on our Web Pages is Universal (UTC)

Universal Alaska Pacific Mountain Central Eastern

Graphics by Modzelewski.

Weather Forecast Research Team, UBC

See our suite of model runs, at:

http://weather.eos.ubc.ca/wxfcst/html-etc/model-metadata/summary.html

We run some models on our own hardware, and others on Google Cloud.

Graphics by Modzelewski.

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Ways to Create the Ensemble-based Deterministic Fcsts

- Use average.
- Use weighted average (e.g., weighted inversely by error variance).
- Use median.
- Use nonlinear combinations of ensemble members.
- Use Gene-Expression Programming (GEP), see Bakhshaii & Stull 2009 WAF.
- Use analog ensembles.

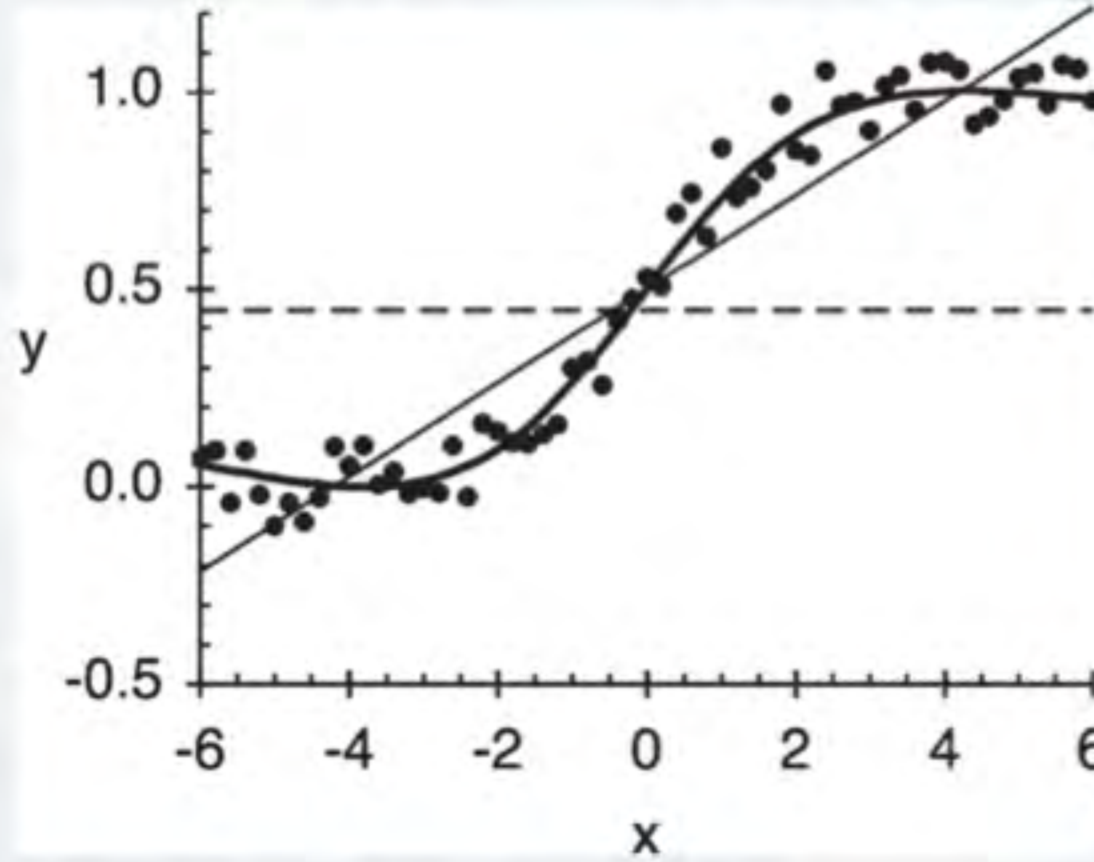
Deterministic Ensemble Forecasts (DET)

- Simple (linear) ensemble mean:
  $T_{ens} = (1/N)\ [T_{model1} + T_{model2} + T_{model3} + \ldots + T_{model\ N}]$
- Example of nonlinear DET from GEP (see next pages.)

A GEP Function Fitting problem

Generation	GEP Chromosome	GEP Equation	Simplified Equation
a) 14	/ a b . . .	$y = a/b$	$y = 0.4452$
b) 68	* x / / a - + a x x x . . .	$y = x \cdot \left[\frac{\left\{ \frac{a-x}{x+x} \right\}}{a} \right]$	$y = 0.5 + 0.119x$
c) 3967	*x//a-+axx+/x*-+x//xababx...		

$$y = x \cdot \left[\frac{\left\{ \frac{a-x}{x + \frac{(x+a)x}{(b/a)-(b/x)} + x} \right\}}{a} \right] \qquad y = \frac{(x+3.7856)/3.7856}{2 + 0.466x\left(\frac{x-3.7856}{x+3.7856}\right)}$$

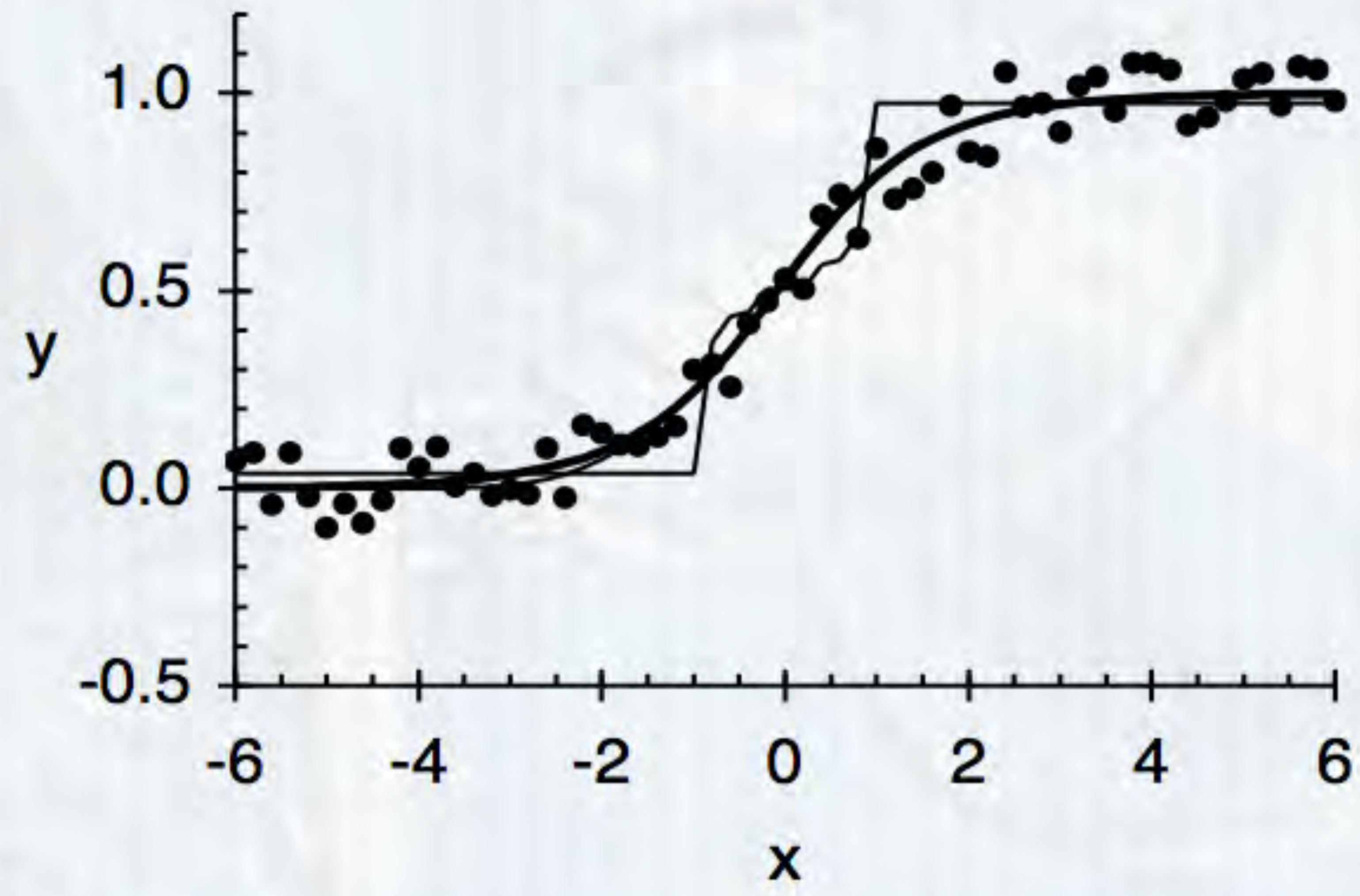


In this illustration, GEP was allowed to use only +, –, *, / .

Examples of non-unique fits by GEP to the synthetic sigmoid data

In this illustration, GEP was allowed to use only:

- (+, –, L) where L is the logistic function $L(x) = \{1 + \exp(-x)\}^{-1}$ (thick line)
- (+, – , Power) (thin dashed line, mostly hidden behind the thick line)
- (+, –, mod) where "mod" is the floating-point remainder (thin solid line)



These illustrations show how GEP inexorably approaches a best fit, even when forced to use non-optimum functions.

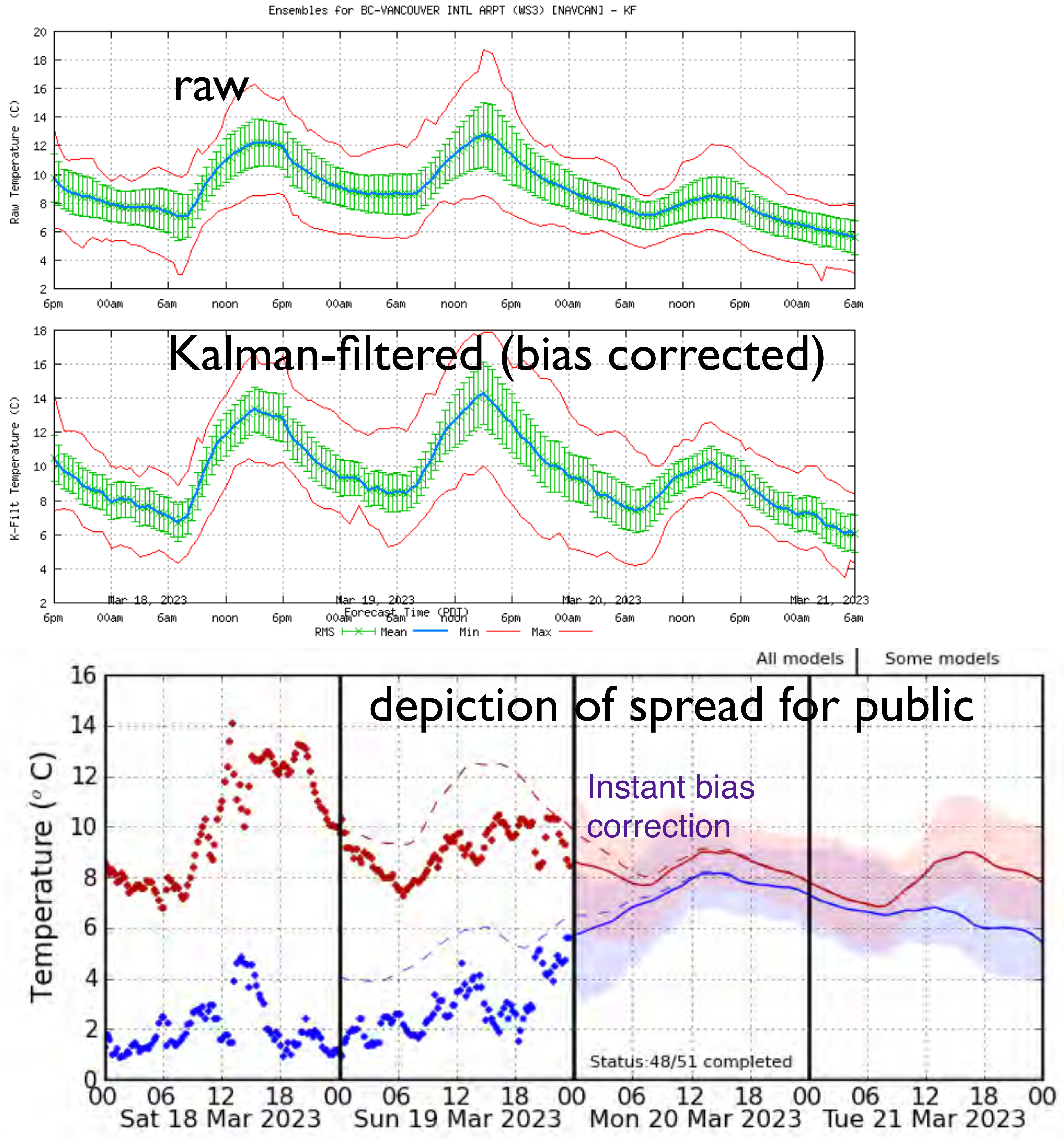
APPENDIX C

Sample MATLAB Algorithm Output from GEP for Vancouver Airport

To save space, some MATLAB constants and functions below are unwrapped into fewer lines.

```
%-----------------------------------------------------------------
% Code generated by GeneXproTools 4.0 on 26/03/2008 1:23:08 PM
% Training Samples:   107
% Testing Samples:    51
% Fitness Function:   RRSE
% Training Fitness:   714.678659643746
% Training R-square:  0.841252910884905
% Testing Fitness:    705.930293551433
% Testing R-square:   0.866029597576304
%-----------------------------------------------------------------

function result = gepModelMC2_B4(d)

G1C0 = 5.990876;      G1C1 = -1.094085;
G2C0 = -5.673554;     G2C1 = 9.717987;
G3C0 = -3.039306;     G3C1 = 7.360748;
G4C0 = 2.495819;      G4C1 = 0.265594;
G5C0 = -1.094085;     G5C1 = -9.883149;
G6C0 = 2.437042;      G6C1 = -3.355499;
G7C0 = -8.08081;      G7C1 = -7.842102;

MC2_108km = 1;  MC2_12km = 2;   MC2_36km = 3;   MC2_4km = 4;
MM5_108km = 5;  MM5_12km = 6;   MM5_36km = 7;   MM5_4km = 8;
WRF_108km = 9;  WRF_12km = 10;  WRF_36km = 11;

varTemp = 0.0;

varTemp =
gepNET2E(gepOR4((gepGT2B(gepLT2B(G1C1,d(MC2_4km)),tanh(d(WRF_12km)))*g
epET2C(d(MC2_36km),G1C0)),d(MM5_36km)),(gepNET2E(tanh(d(MC2_12km)),gep
OR1(G1C1,d(WRF_36km))-
gepOR6(d(MM5_12km),gepLT2A(d(WRF_12km),d(MM5_108km)))));

varTemp = varTemp +
(gepLOE2B(d(MC2_36km),floor((d(WRF_12km)*gepOR3((gepLOE2G((G2C1^G2C1),
gepLOE2B(G2C1,d(MM5_36km)))),gepOR3(gepGau(gepET2A(G2C0,d(WRF_12km))),
(G2C1^3))))))^2);
varTemp = varTemp + atan((gepLT2F(d(MC2_36km),d(MC2_108km))-
gepOR4(gepGOE2B(acot(gepLOE2G(gepOR5(d(MM5_12km),G3C1),gepLT2B(d(WRF_1
08km),d(WRF_36km)))),d(MC2_108km)),exp((0.0)))));

varTemp = varTemp + (-
(gepNET2C(gepGT2B(gepLT2F(gepET2A(gepAND5(d(MM5_4km),G4C0),(d(WRF_12km
)+d(MC2_108km))),gepLOE2E(atan(d(MM5_36km)),d(MC2_4km))),(gepAND3(d(MM
5_108km),d(MC2_108km))+gepGT2C(d(MM5_4km),d(MC2_12km)))),gepNET2G(G4C0
,d(MC2_4km)))));

varTemp = varTemp +
atan((floor(gepLOE2G(gepMin3(gepGOE2B(d(WRF_108km),d(WRF_108km)),(d(MM
5_108km)-
d(MM5_12km)),G5C1),d(MC2_108km)))*gepGT2C(gepET2C(gepAND3(G5C0,d(MC2_1
2km)),d(MC2_12km)),(gepOR4(d(WRF_12km),d(MM5_12km))+tan(d(WRF_36km))))
));

varTemp = varTemp + sech(((-
((gepLT2D(gepOR6(((gepOR1(G6C0,d(WRF_12km))+gepLT2F(d(MC2_12km),d(WRF_
12km)))/2),atan(d(MM5_36km))),sech(d(MC2_36km))^2)))*gepLT2C(G6C0,d(M
C2_4km))));

varTemp = varTemp +
gepET2A(sqrt(gepET2B(gepOR4(d(MC2_36km),gepOR4(tan(d(MC2_108km)),gepNE
T2E(d(MC2_12km),d(WRF_108km)))),acsch(gepOR2(coth(G7C0),d(MC2_12km))))
),gepMin3(d(WRF_108km),d(MC2_4km),d(MM5_108km)));

result = varTemp;


function result = gepMin3(x, y, z)
result = min(min(x,y),z);

function result = gepOR1(x, y)
if ((x < 0) | (y < 0)), result = 1; else   result = 0; end

function result = gepOR2(x, y)
if ((x >= 0) | (y >= 0)), result = 1; else result = 0; end

function result = gepOR3(x, y)
if ((x <= 0) | (y <= 0)), result = 1;  else  result = 0; end

function result = gepOR4(x, y)
if ((x < 1) | (y < 1)), result = 1;  else  result = 0; end

function result = gepOR5(x, y)
if ((x >= 1) | (y >= 1)),  result = 1;  else result = 0; end

function result = gepOR6(x, y)
if ((x <= 1) | (y <= 1)), result = 1; else result = 0; end

function result = gepAND3(x, y)
if ((x <= 0) & (y <= 0)), result = 1; else result = 0; end

function result = gepAND5(x, y)
if ((x >= 1) & (y >= 1)), result = 1; else result = 0; end

function result = gepLT2A(x, y)
if (x < y), result = x; else result = y; end
```

Sample Ensemble-Average Meteogram from UBC



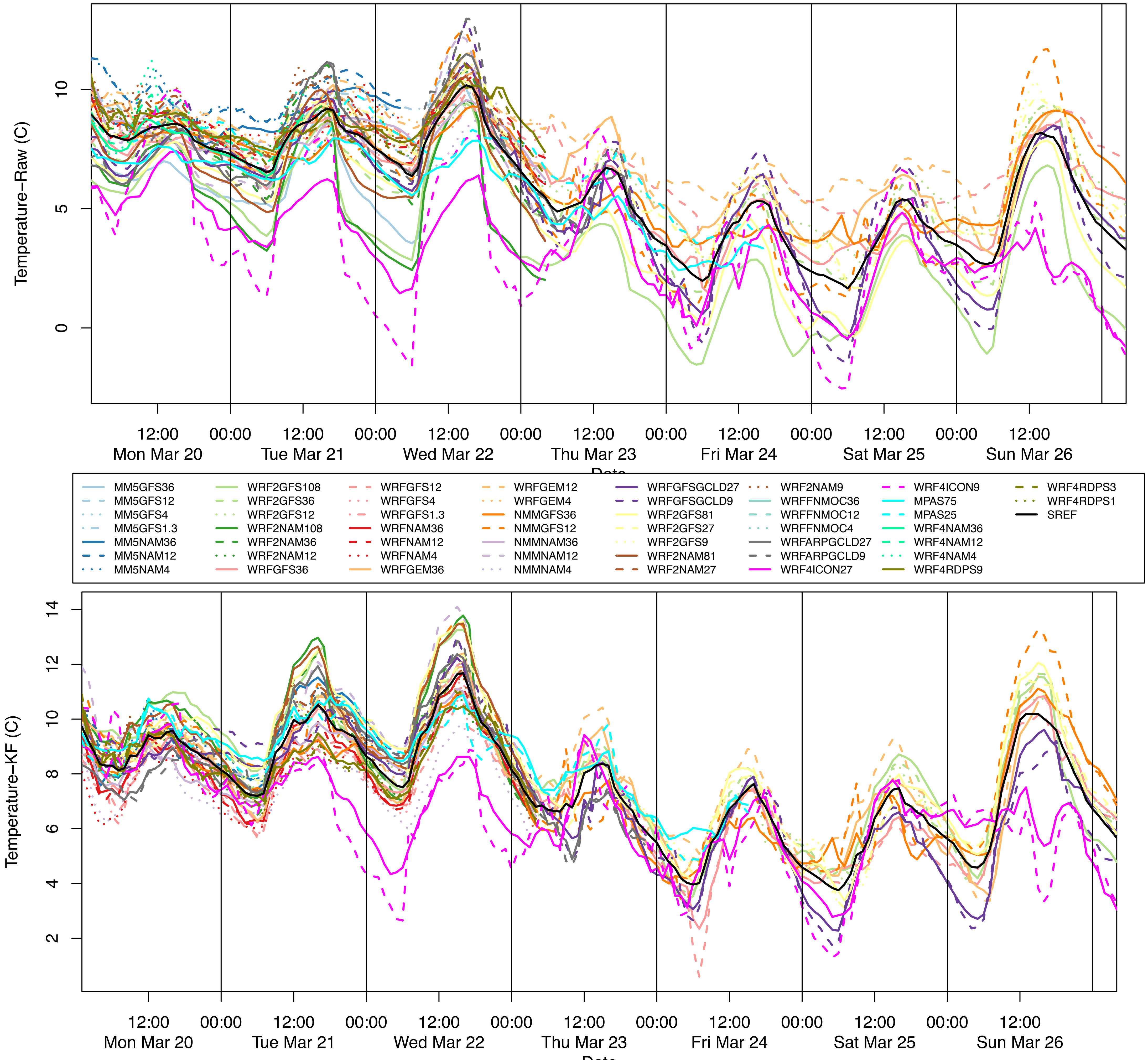
Spaghetti diagrams

(UBC Ensemble Forecast)

(top) Raw temperature forecasts for Vancouver.

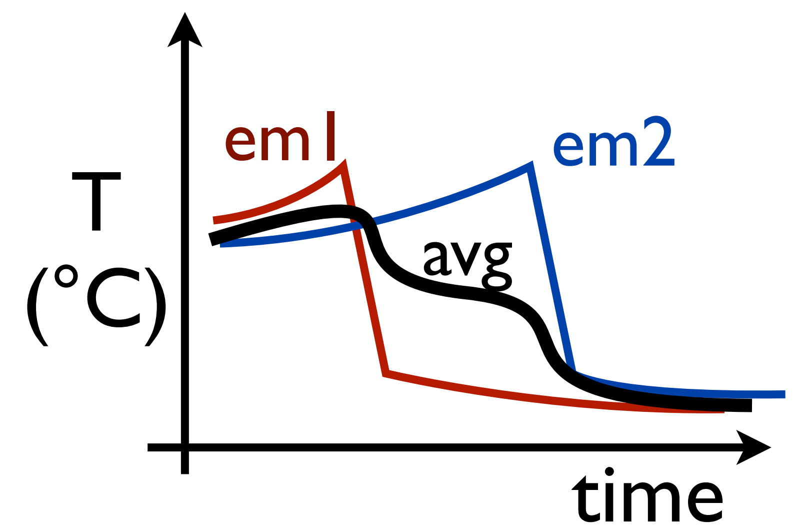
(bottom) Temperatures of each model are first bias-corrected using a Kalman filter

For both plots, the black line is the ensemble average (SREF)



Comments on DEFs (e.g., ensem. averages)

- Ensemble average is physical unrealizable. (E.g., winds don't agree with pressures), but Rachel Steinhart showed they can still be used to initialize NWP models.



- For ensembles sharp features (e.g., fronts) that progress at different speeds, the ensemble average causes unphysical smoothing.
- Ensemble average loses skill during regime changes.
- Bias-correct each member BEFORE combining into an ensemble.
- Ensembles with more (well chosen) members are more accurate than small ensembles. But don't include known bad members.
- Data voids (such as NE Pacific) cause all ensemble members to have similar errors (i.e., small spread NOT due to high confidence of an accurate forecast).
- Imposed lateral boundary conditions can dominate limited-area models (LAMs), resulting in poor ensemble spread.

But why stop with deterministic fcsts ...

- ...when you have so much more info from the ensemble spread?

Outline

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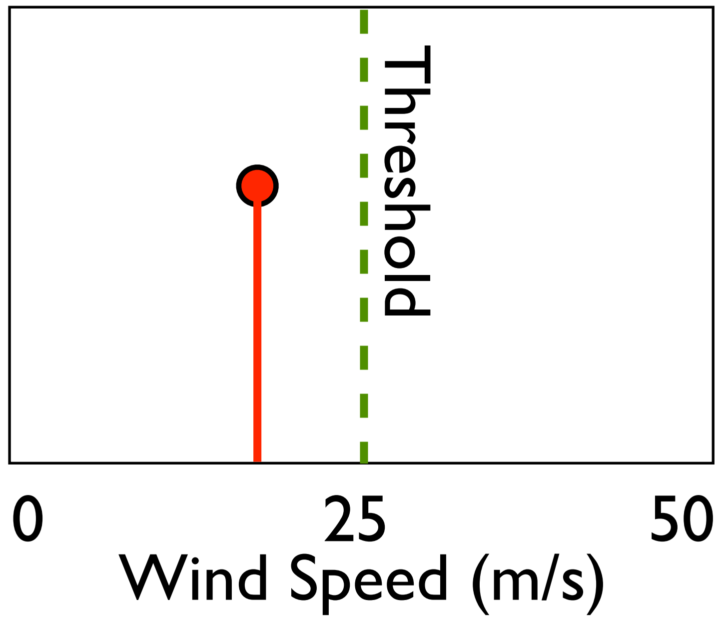
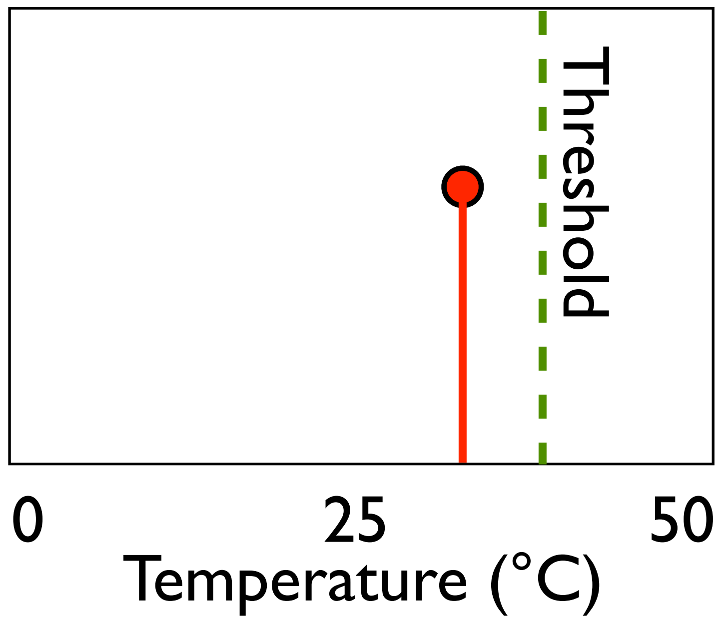
photos by Mark Stull

Deterministic Forecasts

after postprocessing & ensemble-average

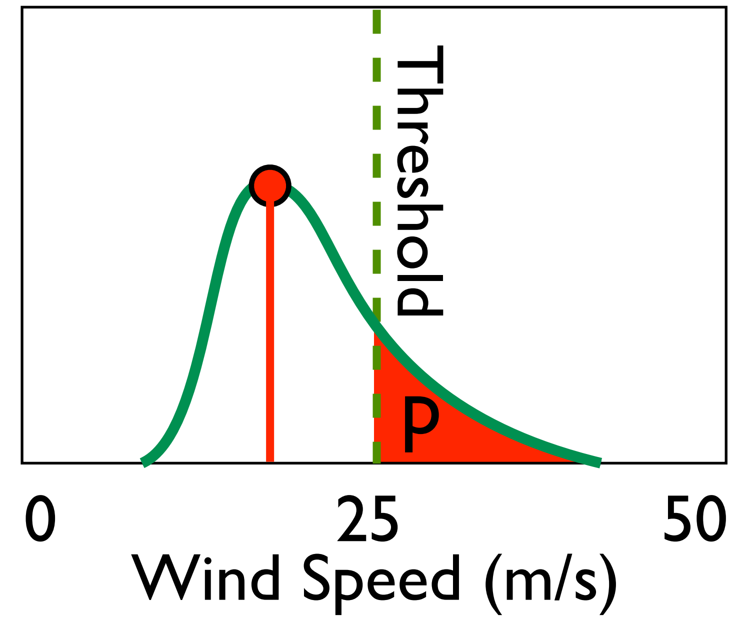


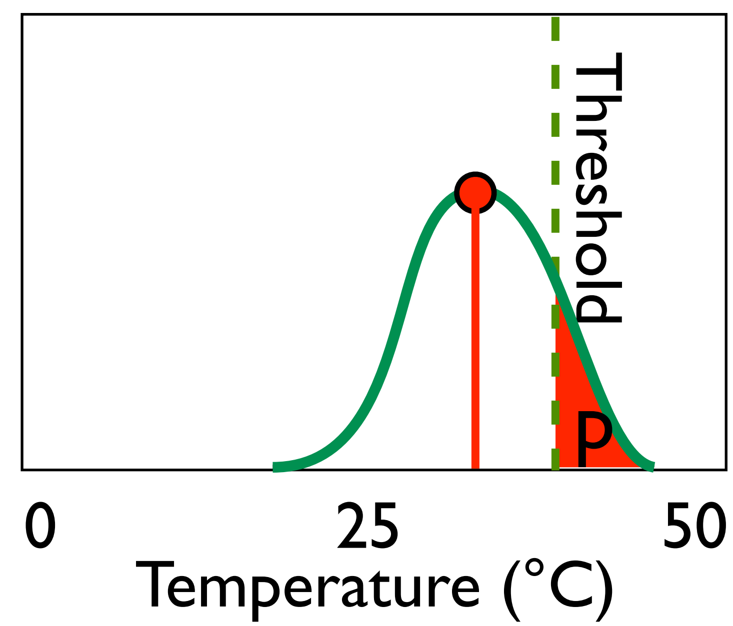


...but the forecast can have errors.

Probabilistic Forecasts

photos by Mark Stull





p = probability of threshold exceedance

Decision-making with Probabilistic Forecasts

Let: C = $$ cost to try to mitigate/avoid an event
L = $$ lost if event happens (without mitigation)

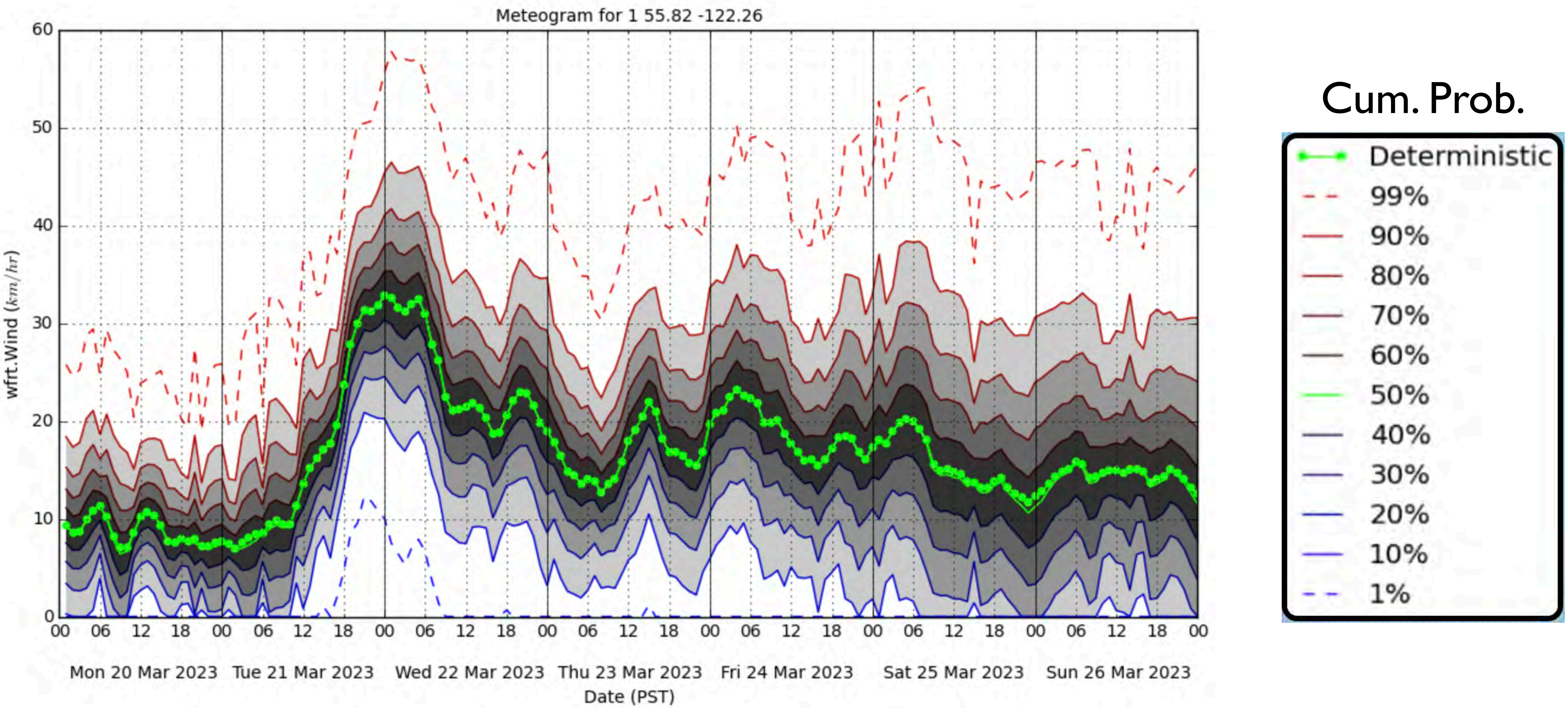
Then: $r = C/L$ cost loss ratio

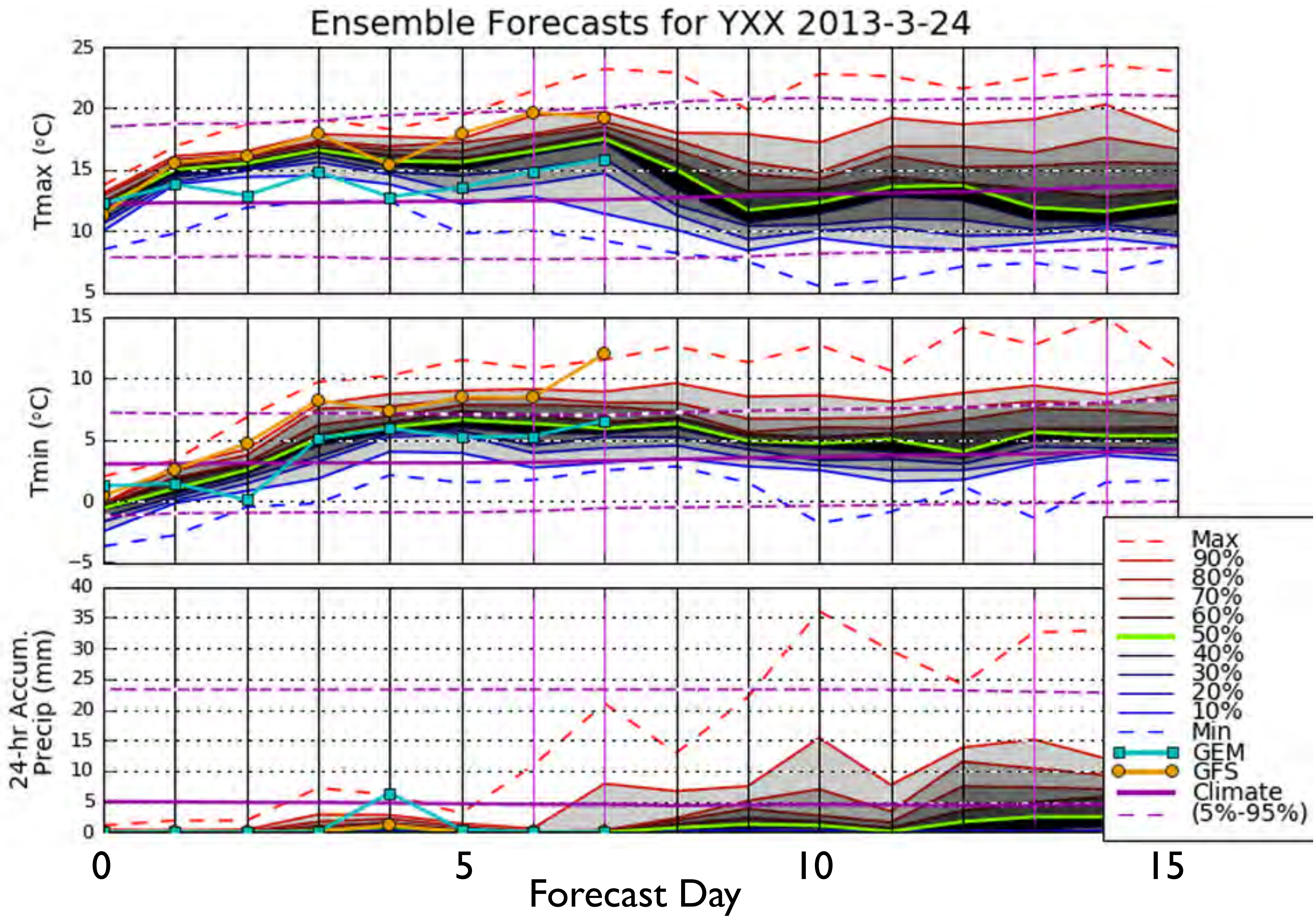
Take action whenever: $p > r$

Namely, take action when: $C < p \cdot L$

E.g.: Loss is $$ needed to replace overheated transmission line.
Cost is $$ not earned by reducing the amperage, or fines.

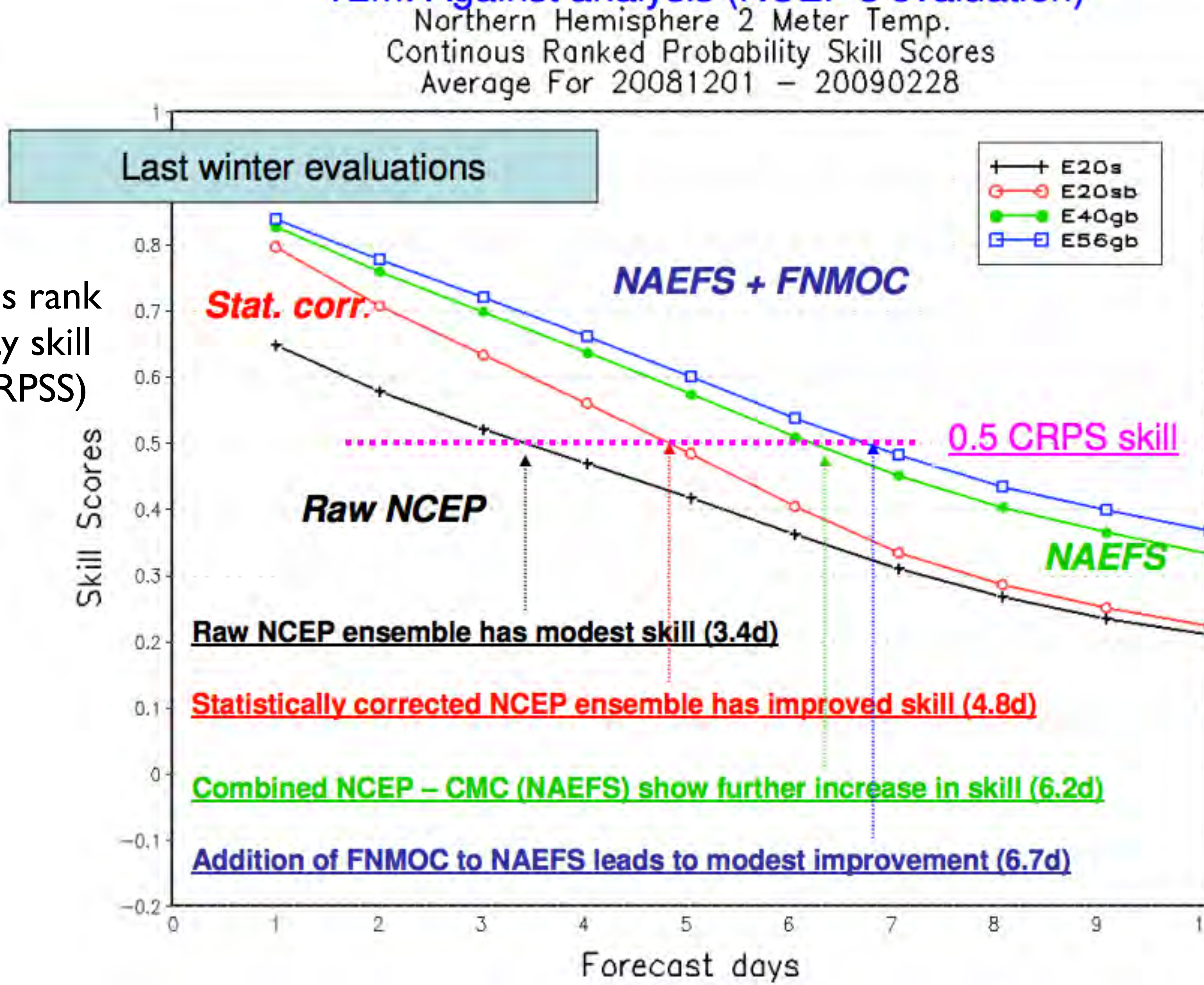
Sample Probability Fcst for a wind farm in BC




Ensemble Forecasts for YXX 2013-3-24
Tmax (°C)
Tmin (°C)
24-hr Accum. Precip (mm)
Max
90%
80%
70%
60%
50%
40%
30%
20%
10%
Min
GEM
GFS
Climate
(5%-95%)
Forecast Day

T2m: Against analysis (NCEP's evaluation)

continuous rank probability skill score (CRPSS)



Zhu & Cui, Jan 2010

Comments on Probability Forecasts

- Needs of meteorologists are different from needs of end users.
- Many industries could use prob. fcsts. to very good economic advantage, but are unable to realize it. (The industry needs a meteorologist on staff to use prob. fcsts.)
- Most lay people are clueless, and think that probability fcsts. are a joke.

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Analog Ensemble

- Method: Use past weather forecasts that best match today's synoptic regime as ensemble members.
- Advantages: handles regime changes better, and automatically eliminates NWP model biases.

Delle Monache, Nipen, Liu, Roux, Stull, 2011, MWR.

Analog Ensemble (AnEn) Method

Traditional AnEns (Fig. 1) use a single numerical weather prediction (NWP) model to make a forecast (*TaFcst*), then search an archive to find a number of past similar “analog” forecasts from that same model (*AnFcsts*), and finally retrieve the observations corresponding to those past forecasts (*AnObs*) to serve as members of an ensemble forecast (*AnObsEn*, i.e., traditional AnEn).

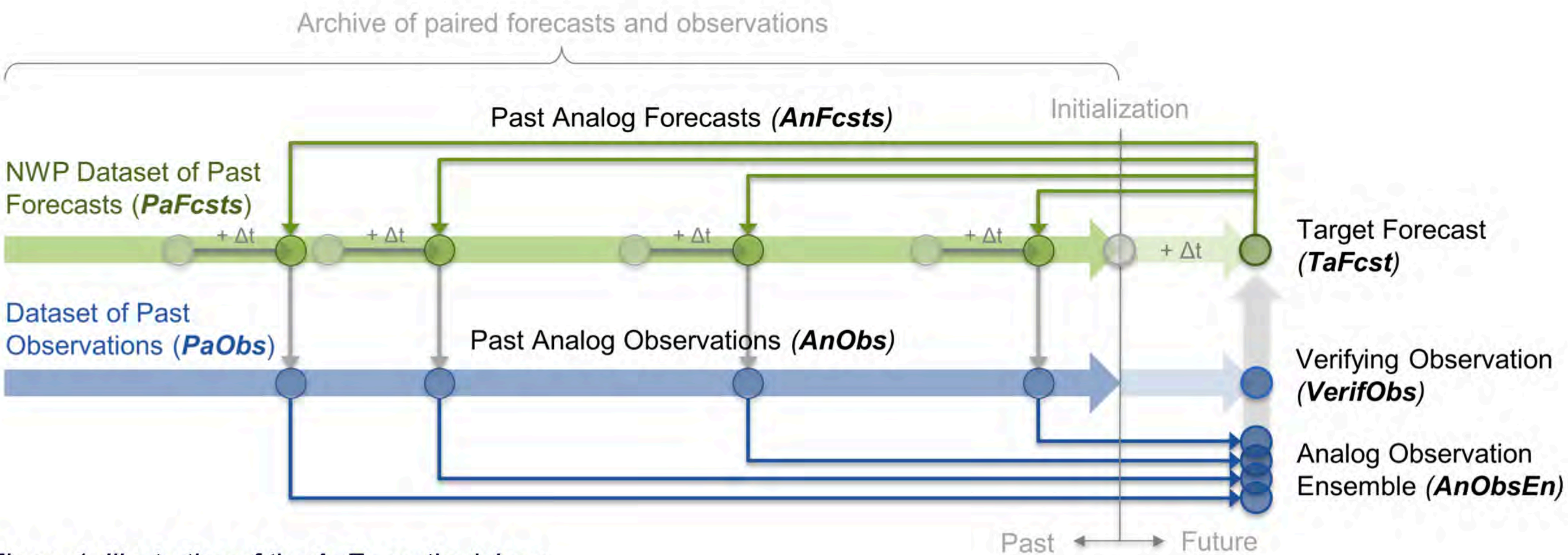


Figure 1. Illustration of the AnEn methodology.

Jeworrek, West, Stull, 2023.

How skillful is AnEn?

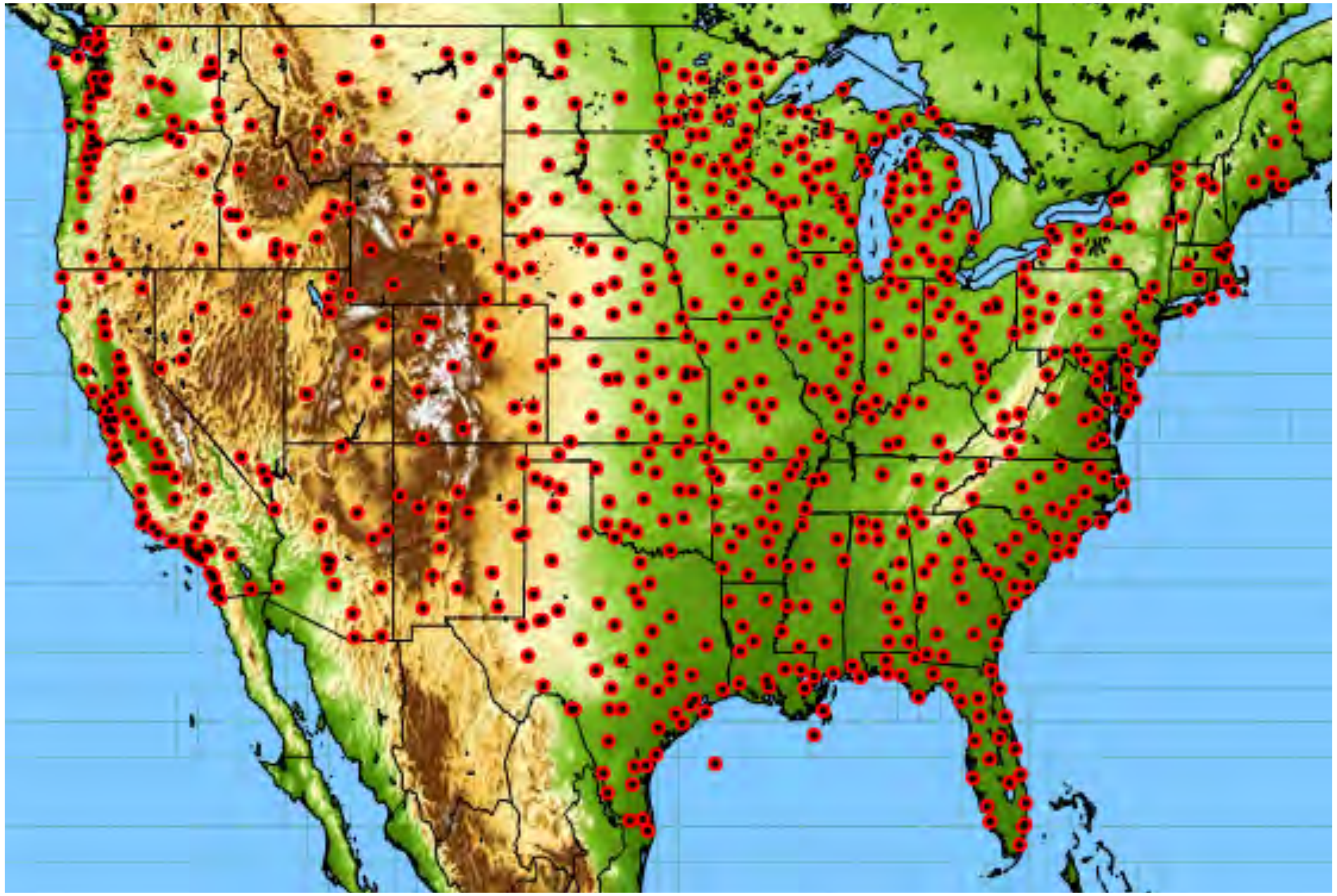
- AnEn generated with Environ. Canada GEM (15 km), 0-48 hours
- Comparison with Environment Canada Regional Ensemble Prediction System (REPS, 20 members, 33 km grid spacing)
- Period of 15 months (verification over the last 3 months)
- 10-m wind speed, 2-m temperature
- 550 surface stations over CONUS
- Probabilistic prediction attributes: reliability & sharpness, statistical consistency, utility/value

Slide modified from originals by Luca Delle Monache, F. Anthony Eckel, Daran Rife, Badrinath Nagarajan, and Keith Searight, (2012), from CMOS conference presentation in Montreal.

Ground truth dataset

- 550 hourly METAR Surface Observations

- 1 May 2010 – 31 July 2011, for a total of 457 days
- 10-m wind speed



Slide modified from originals by Luca Delle Monache, F. Anthony Eckel, Daran Rife, Badrinath Nagarajan, and Keith Searight, (2012), from CMOS conference presentation in Montreal.

AnEn Results

Delle Monache et al 2011, MWR

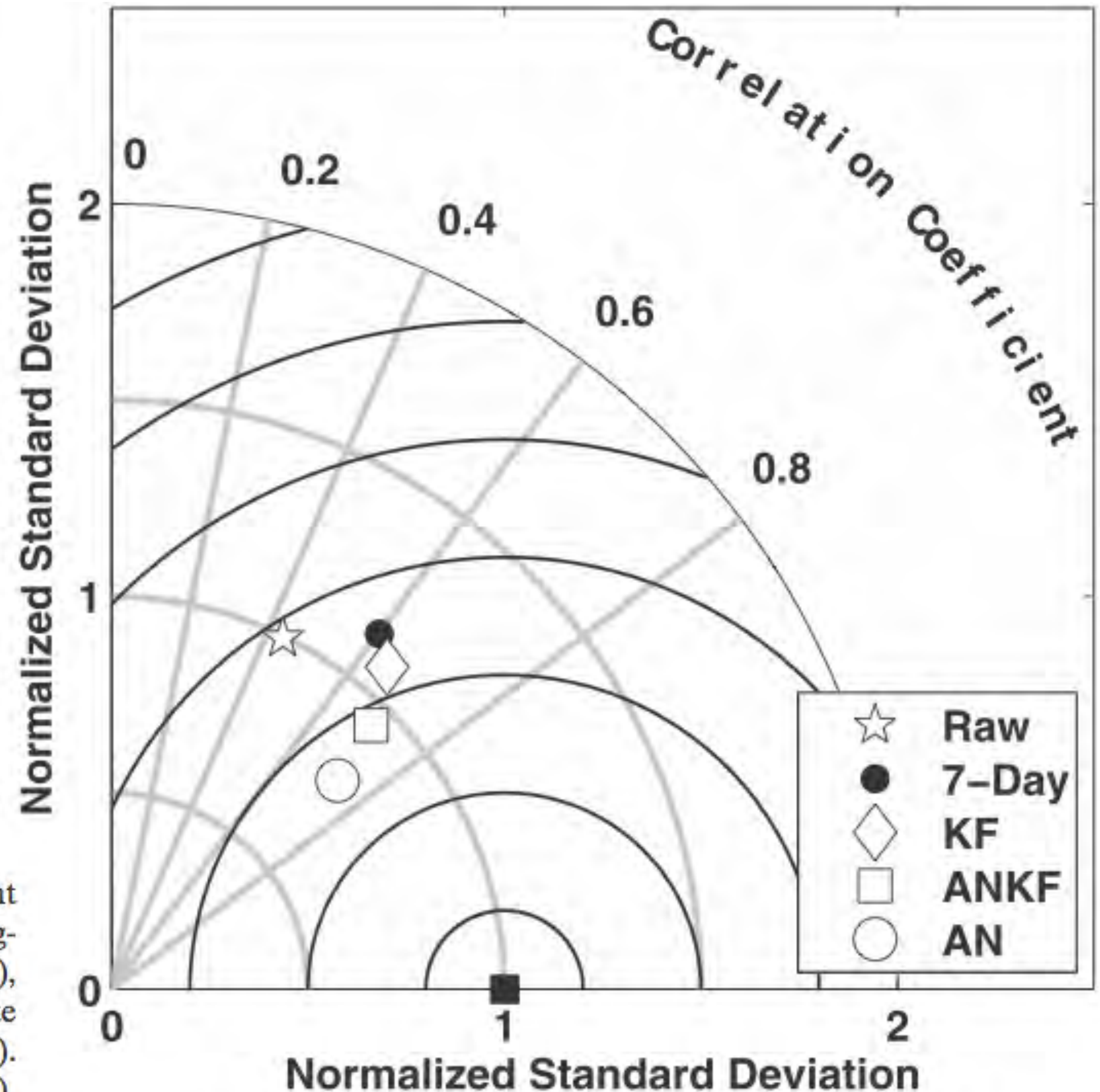


FIG. 5. Taylor diagram showing the raw forecast (Raw, 5-point solid white star), and the postprocessing methods: the 7-day running-mean correction (7-Day, black circles), the KF (white diamonds), KF run through an ordered set of analog forecasts (ANKF, white squares), and the method based only on analogs (AN, white circles). The azimuthal position gives the correlation (straight gray lines), while the radial distance from the origin is proportional to the normalized standard deviation (circular gray lines). The black square represents the observations. The distance between the observation and a given point (black circular lines) is proportional to the CRMSE between the observations and the forecast having the correlation and standard deviation of the given point.

Analog Ensembles (AnEn)

Results: Eckel et al. (2012 CMOS conf., Montreal)

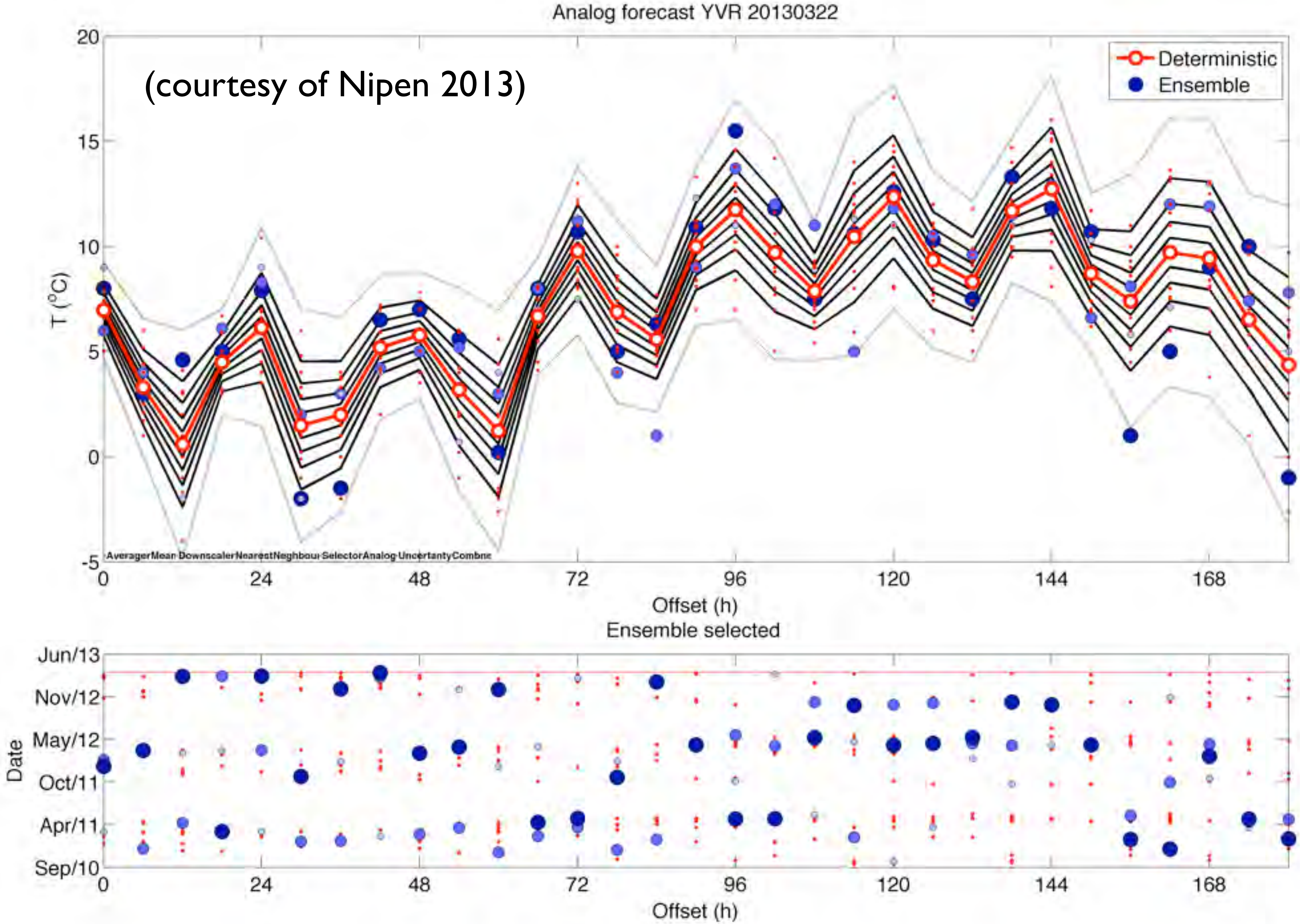
AnEn (from only one NWP run) had comparable verification scores (reliable, sharp, consistent, valuable) as the 20-run GEM ensemble.

AnEn is best at capturing changes in synoptic regime.

THIS COULD BE A GAME CHANGER !!

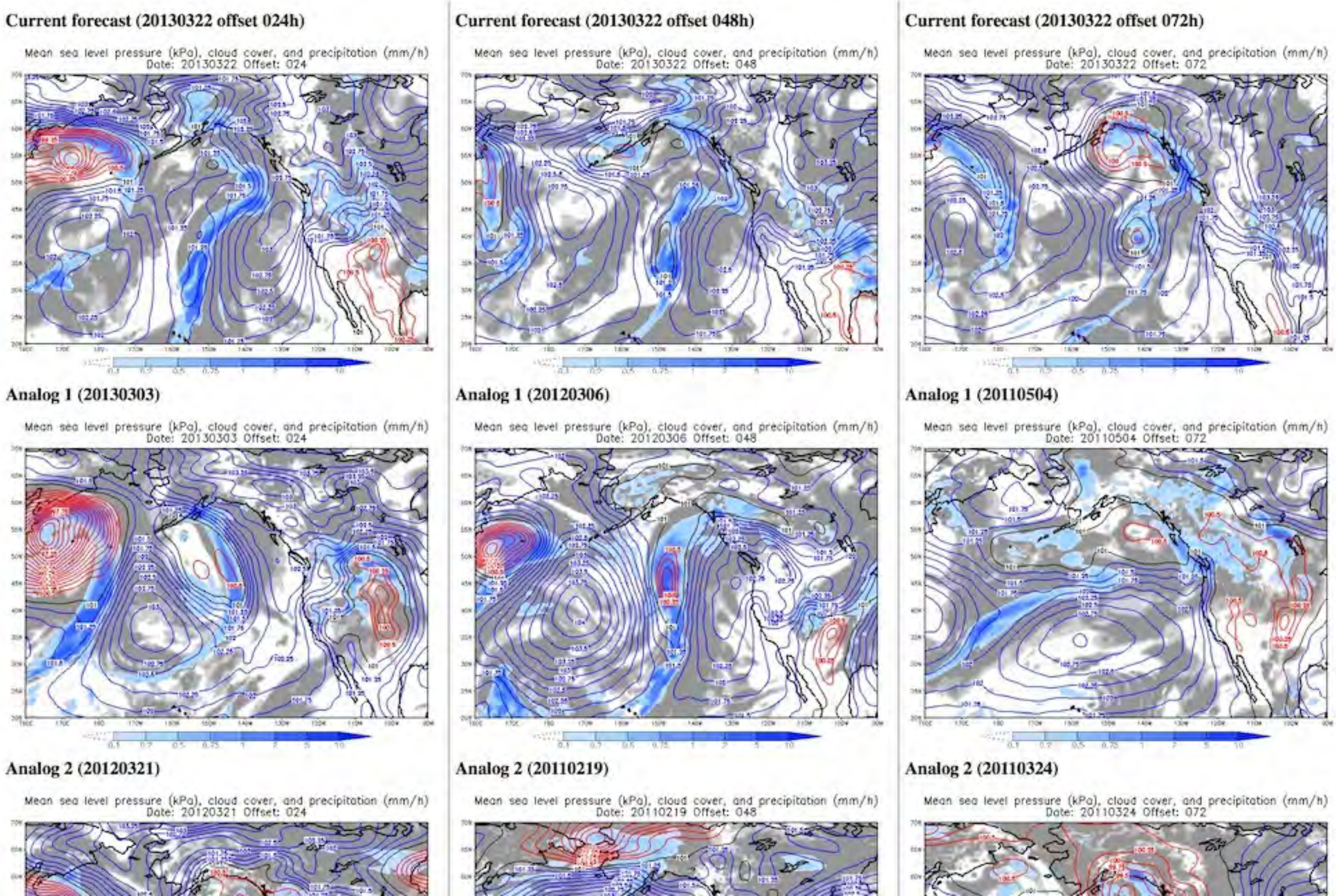
We at UBC are almost ready to start making operational runs of AnEn.

Analog Ensembles became operational at UBC in March 2013



View the synoptics of the best analogs

(courtesy of Nipen 2013)



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(E2E) Ensemble outputs as inputs to other ensemble models

- wx --> CMAQ (for air pollution dispersion)
  See papers by Delle Monache & Stull, 2008, 2006, 2003.

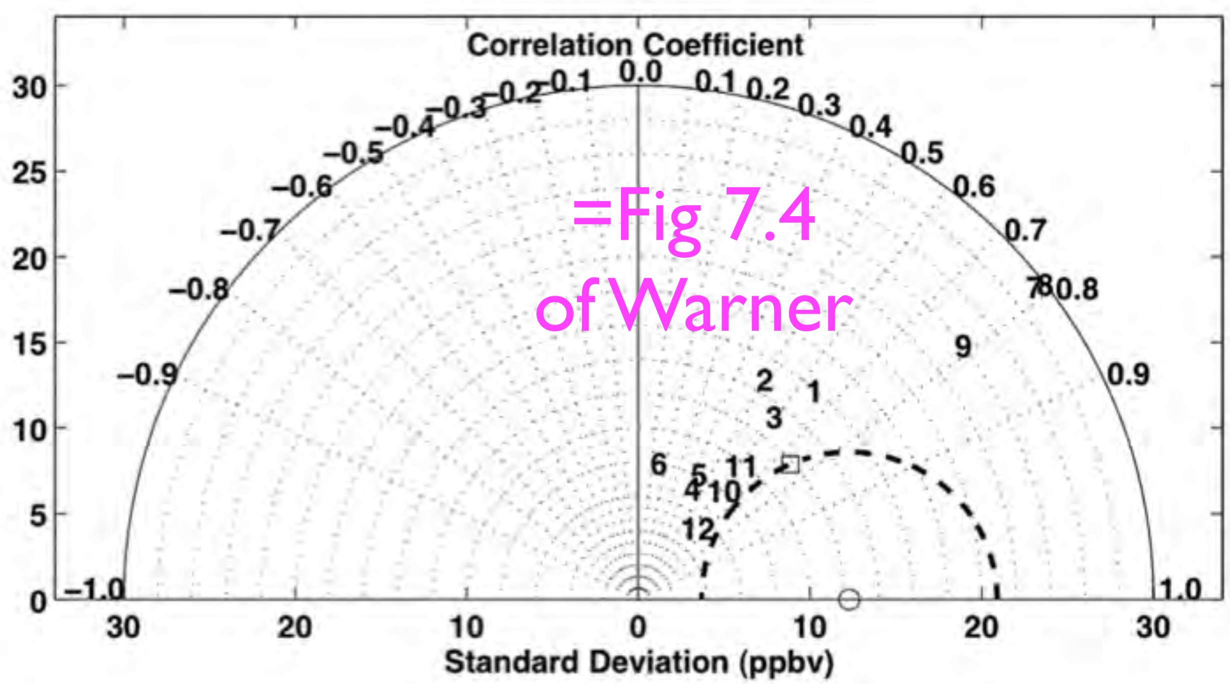


Figure 15. Taylor diagram plotted for Vancouver International Airport (CYVR). The azimu gives the correlation, while the radial distance from the origin is proportional to the standard deviation (ppbv). The circle represents the observations, and the square is the ensemble mean. The numbers correspond to the ensemble member indices. The distance between the observation and a given point is proportional to the centered root mean square error (CRMSE) between the observations and the forecast having the correlation and standard deviation of the given point. The dashed line indicates the ensemble mean CRMSE centered over the point representing the observations.

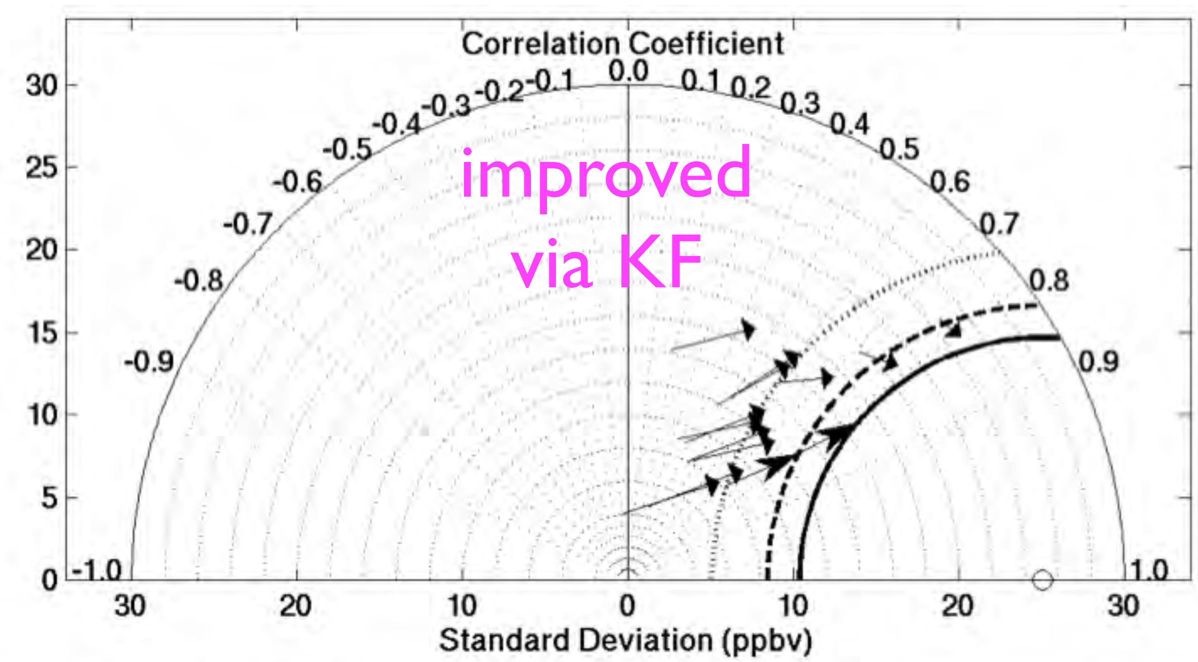


Figure 13. Taylor's diagram for Chilliwack (similar to Figure 8).

E2E - continued

- wx --> hydroloqic
  (for reservoirs)
  See papers by Bourdin & Stull, 2013.

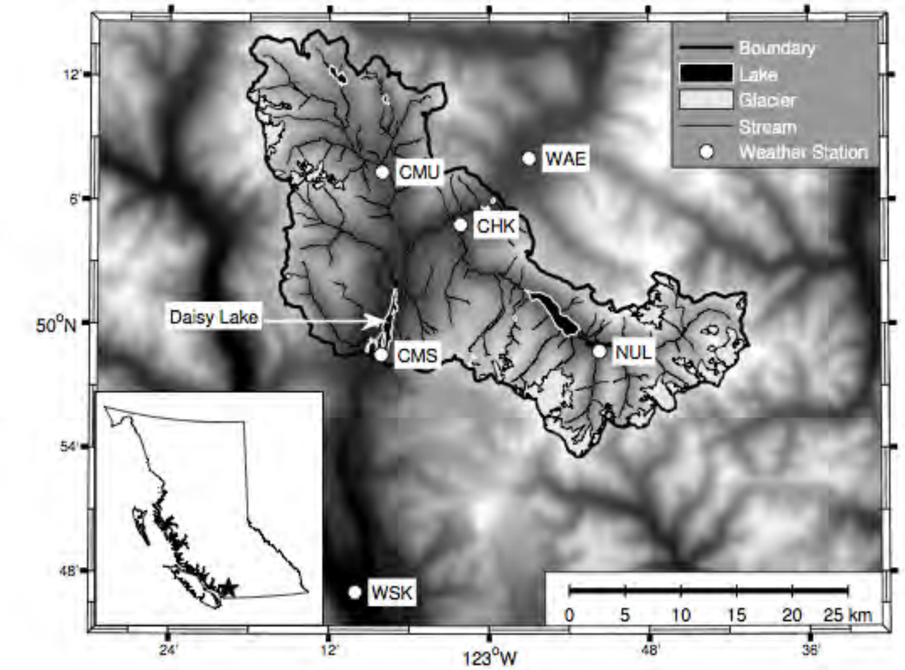
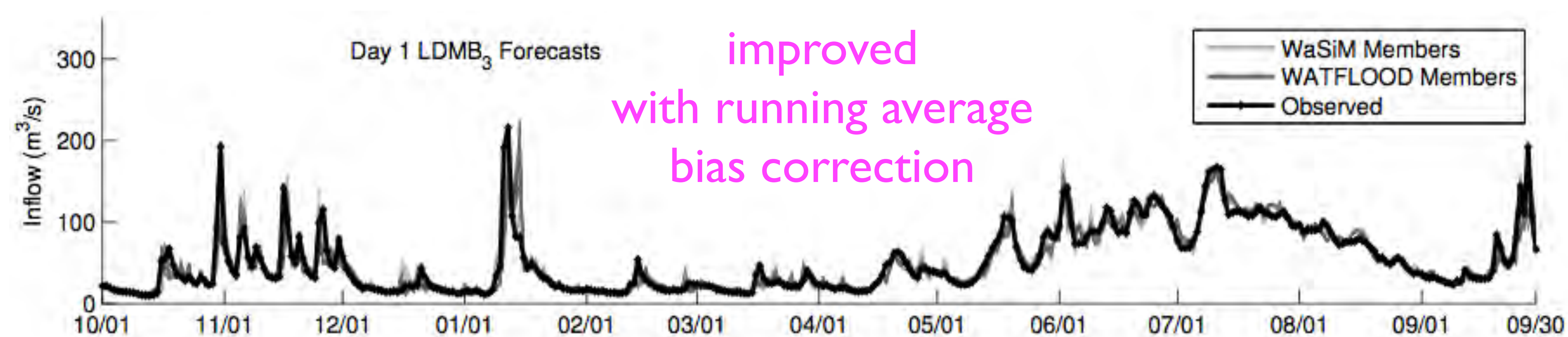


Figure 1: Map of the Cheakamus basin above the Daisy Lake reservoir, located in southwestern BC. Elevations of weather stations (white dots) range from 52 m above sea level (WSK) to 880 m (CMU), while basin terrain ranges from 341 m to 2677 m. ASTER GDEM background



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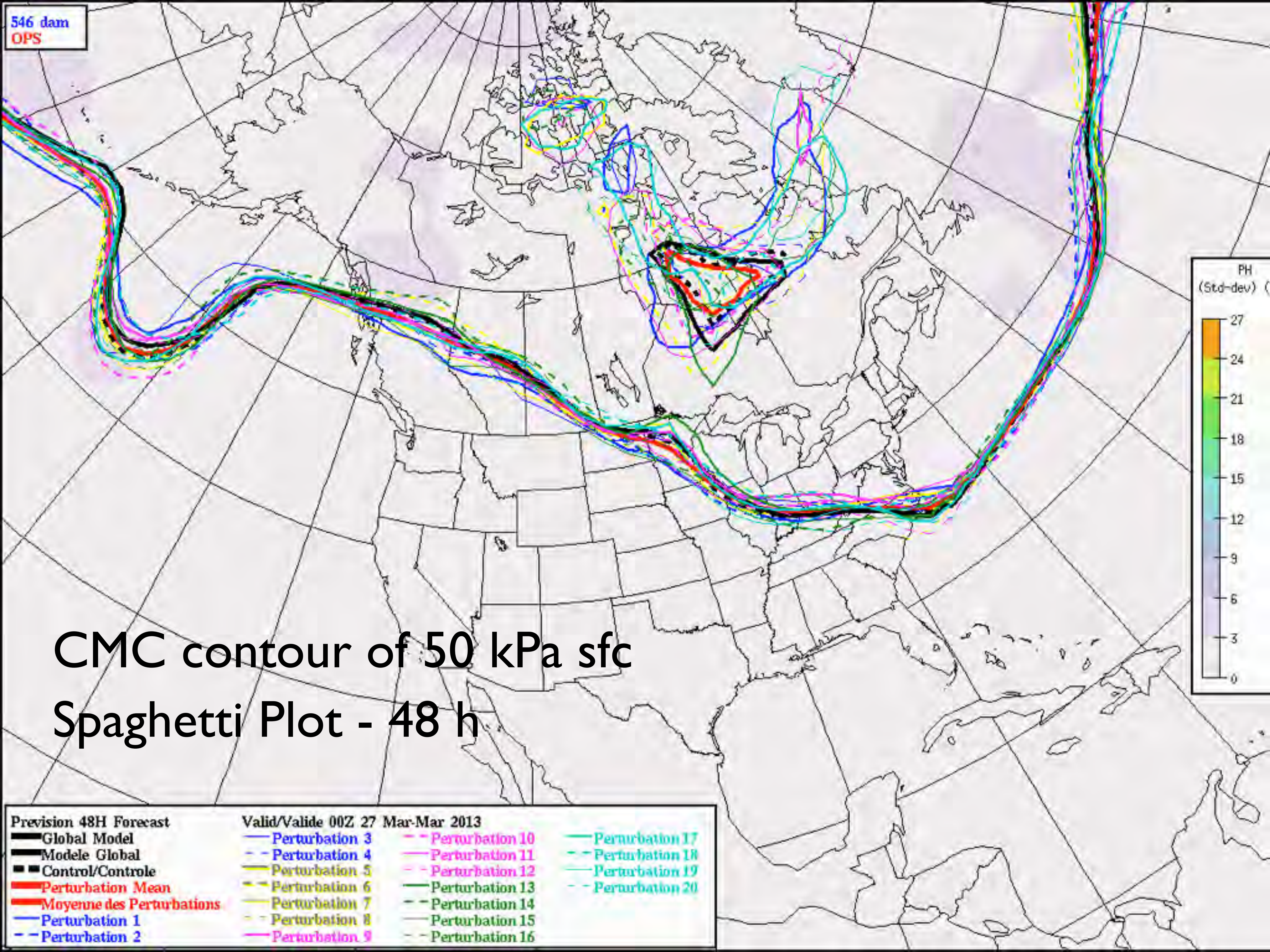
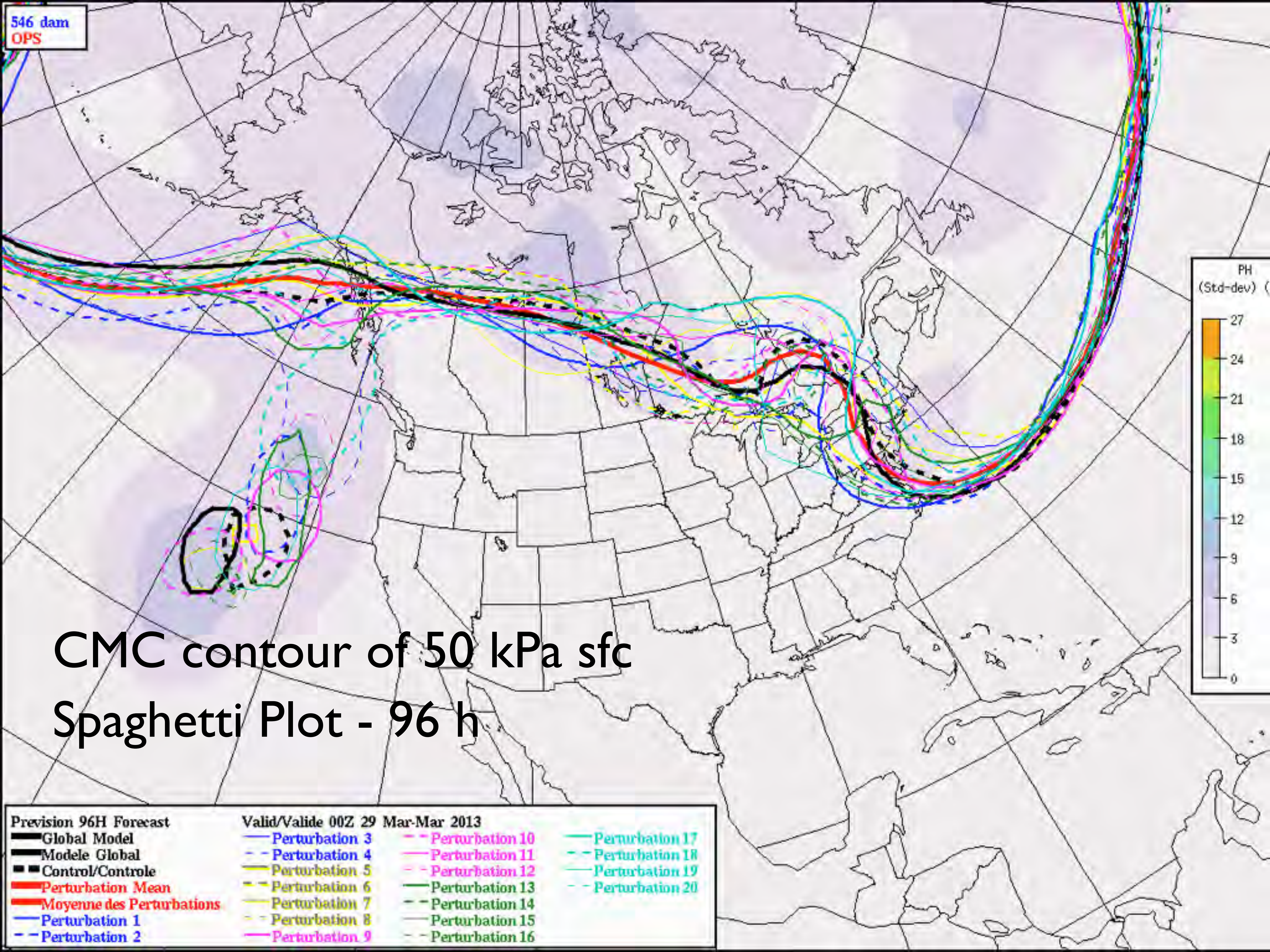


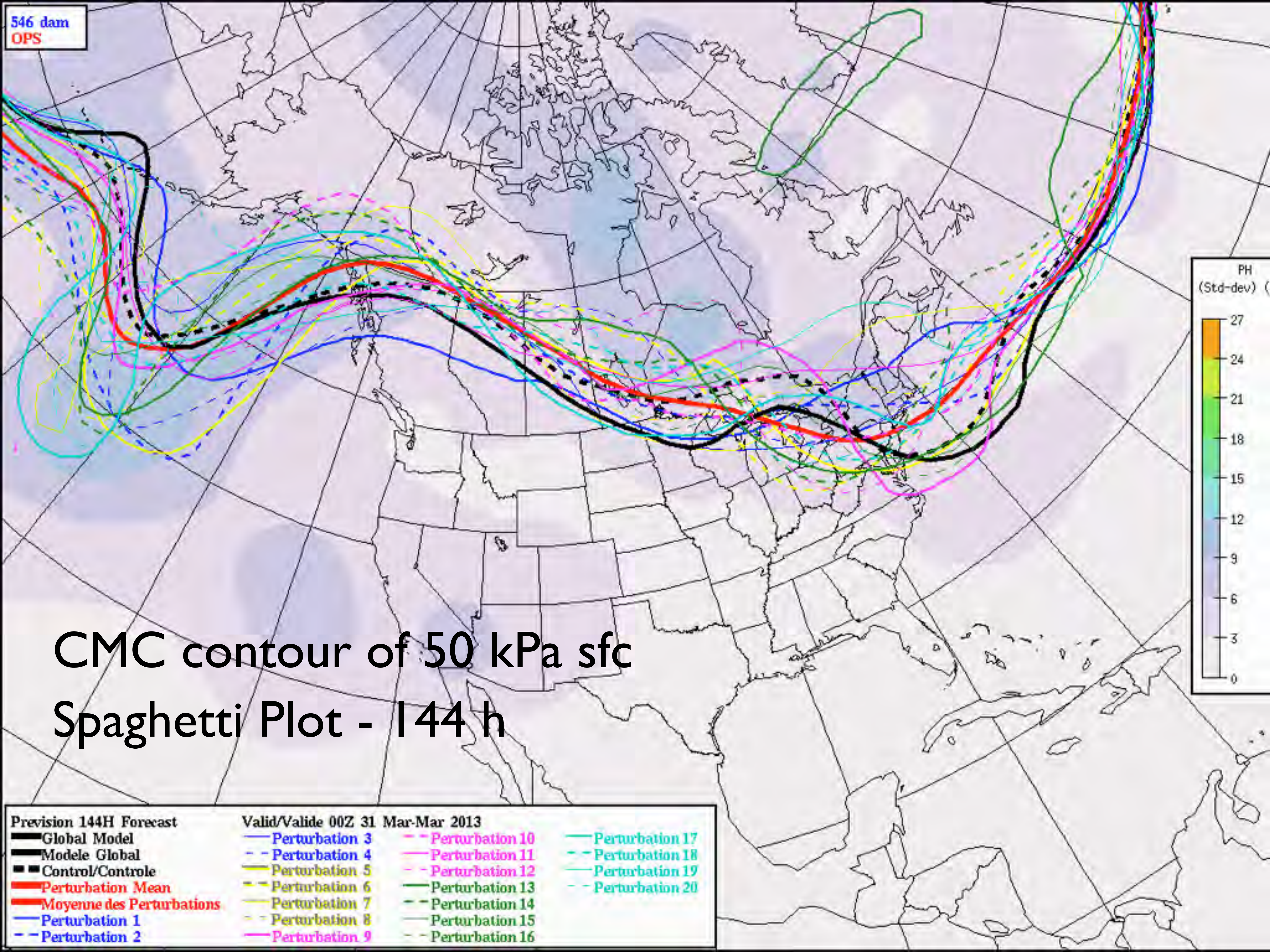
CMC contour of 50 kPa sfc Spaghetti Plot - 48 h

CMC contour of 50 kPa sfc Spaghetti Plot - 96 h

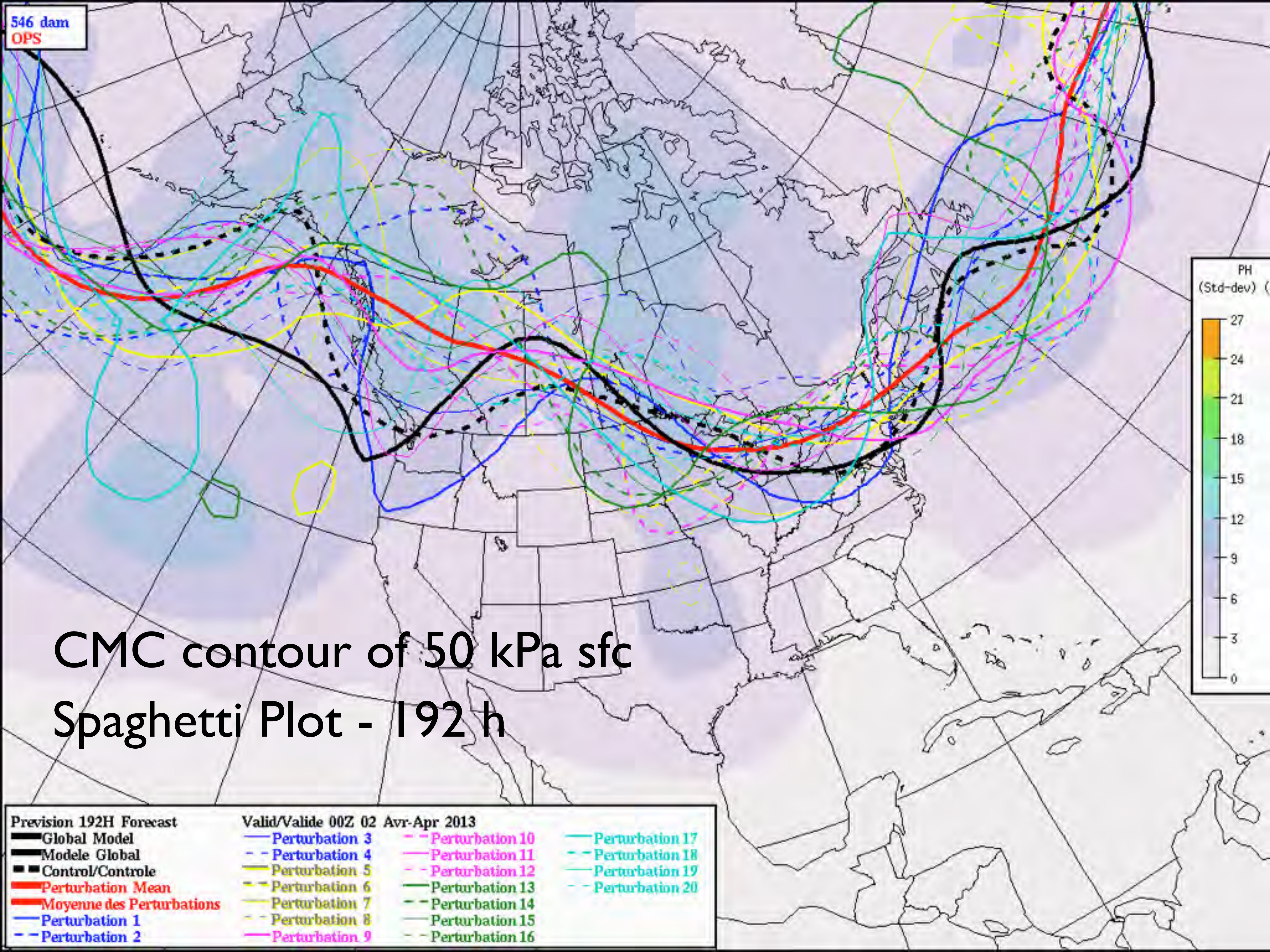


CMC contour of 50 kPa sfc

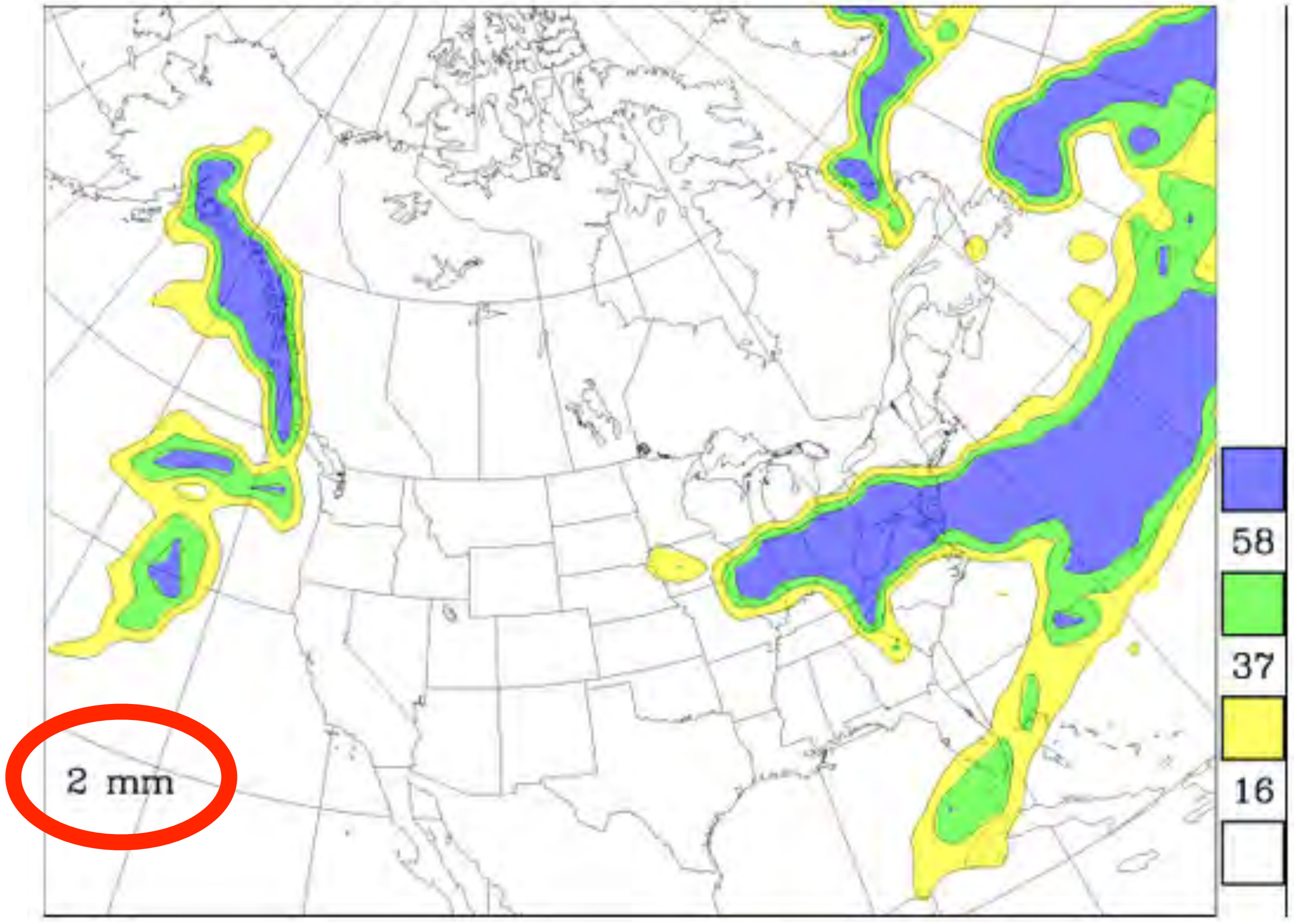
Spaghetti Plot - 144 h

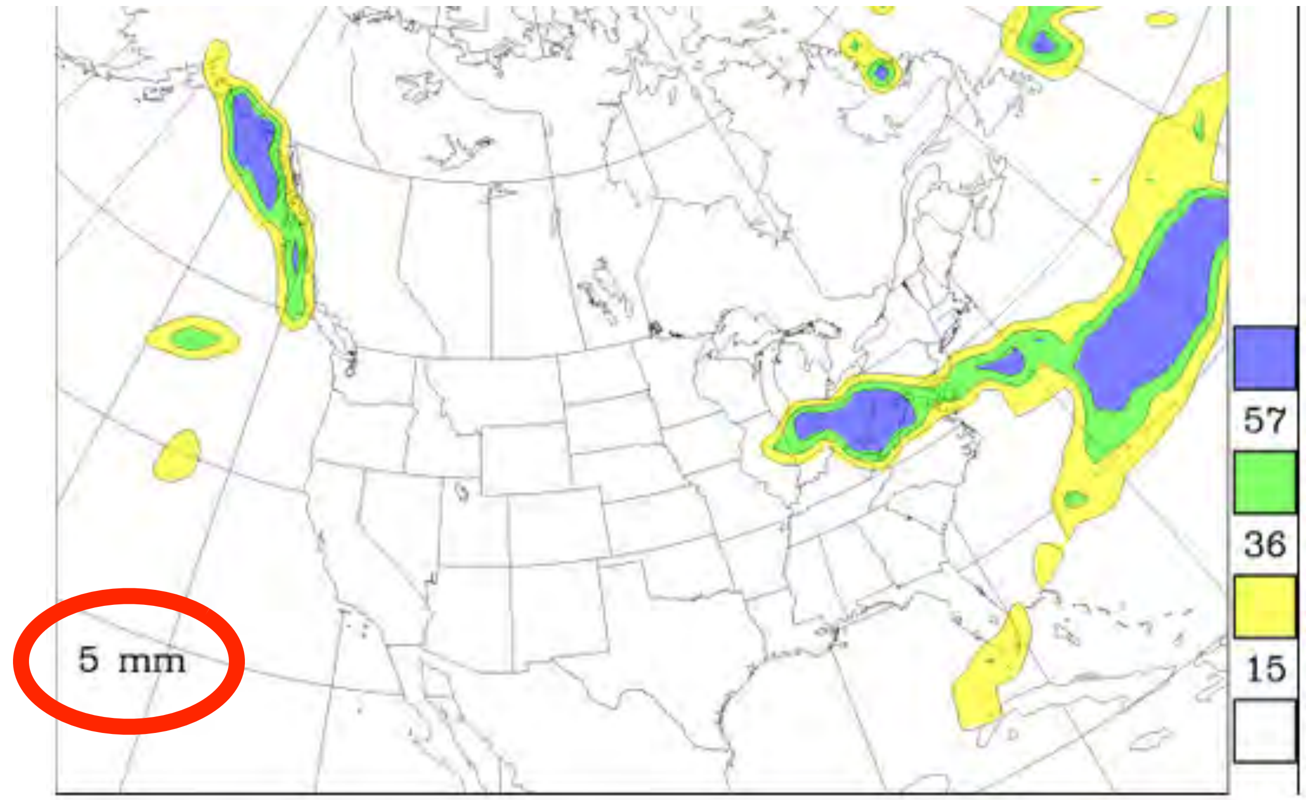


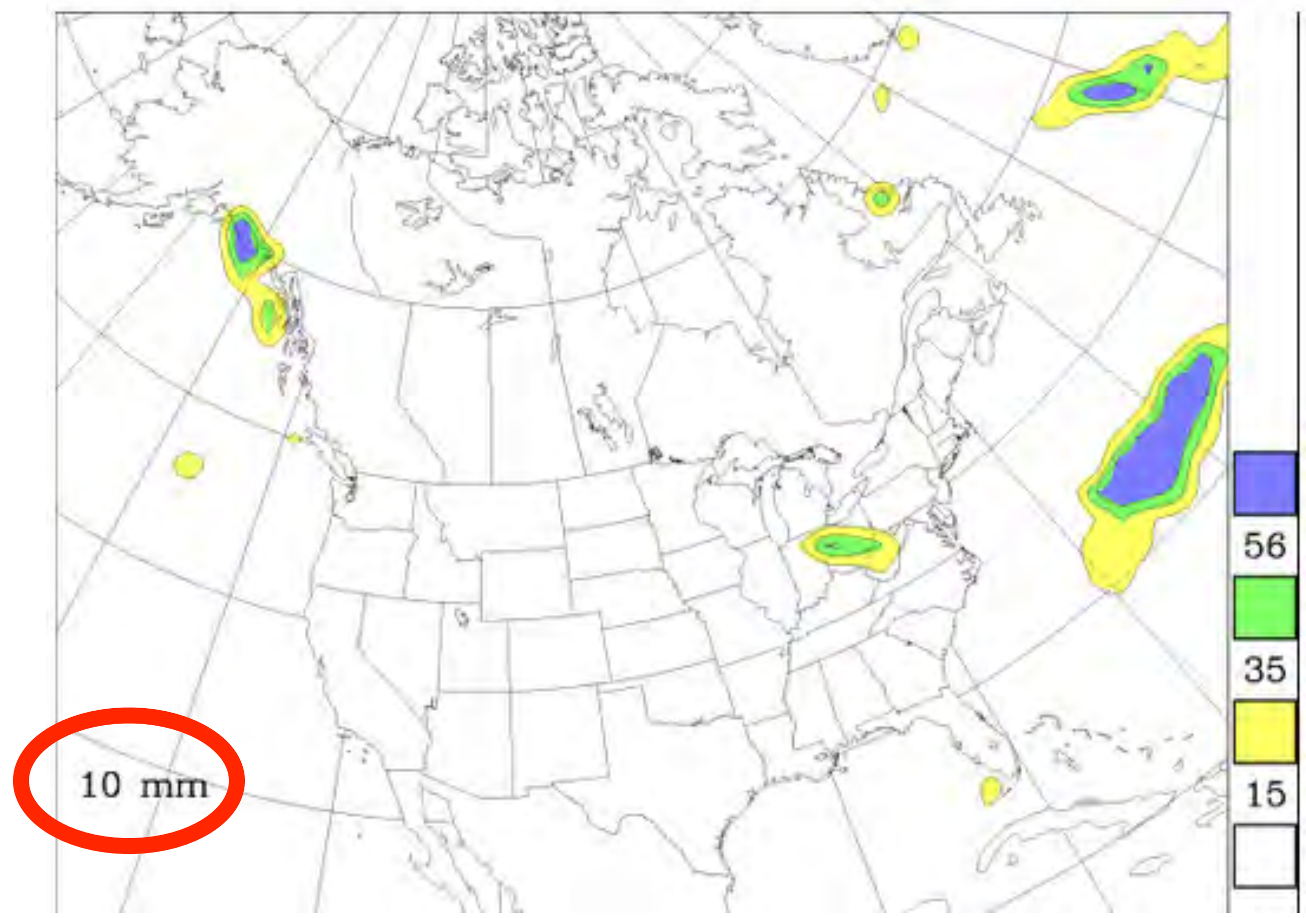
CMC contour of 50 kPa sfc
Spaghetti Plot - 192 h



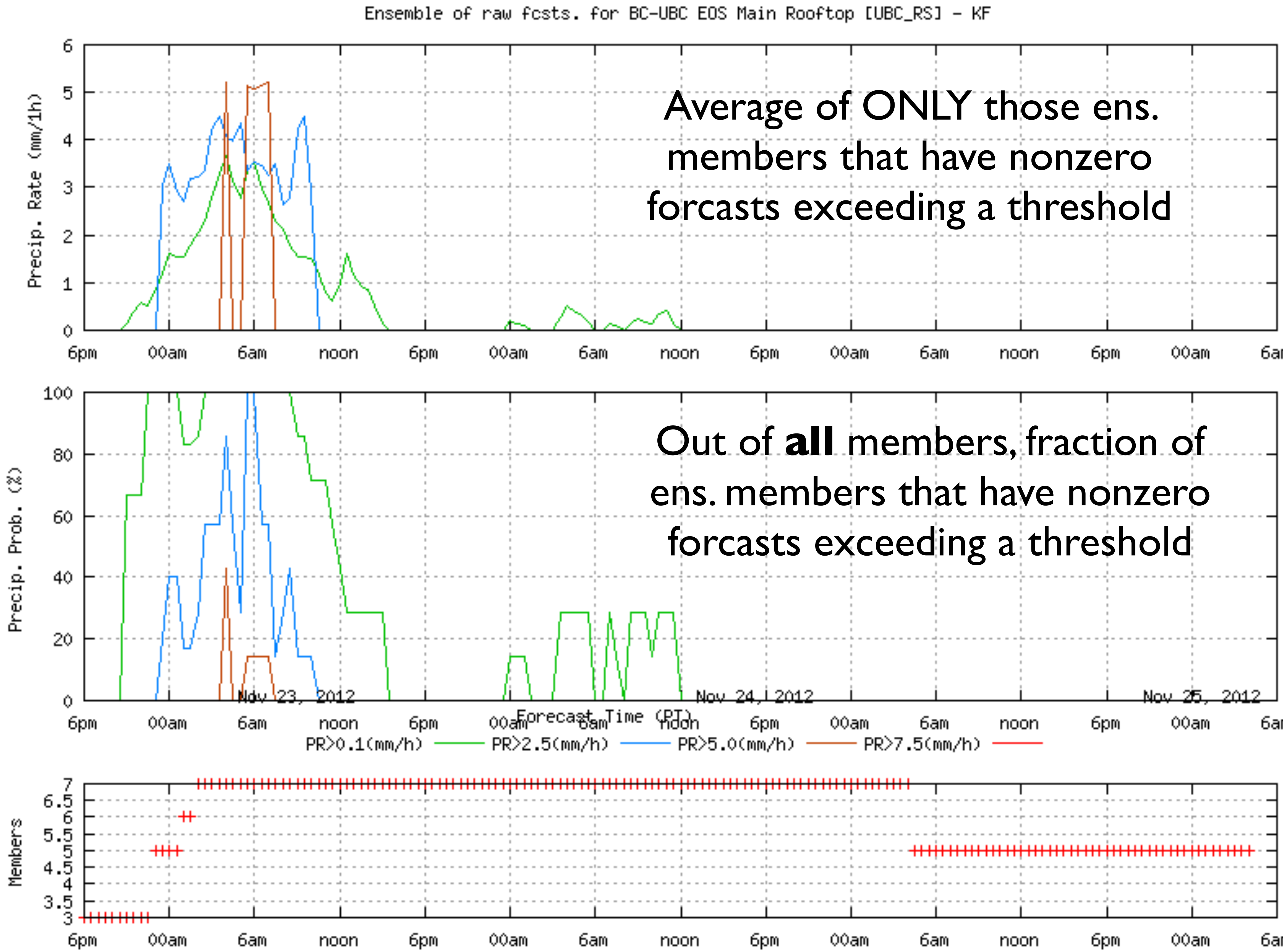
012h forecast of the probability that the 12 hour accumulation exceeds 2mm, 5mm, 10mm or 25mm (The 12 hour accumulation period immediately precedes the validity time)
Valid on Mar 25, 2013 12 UTC



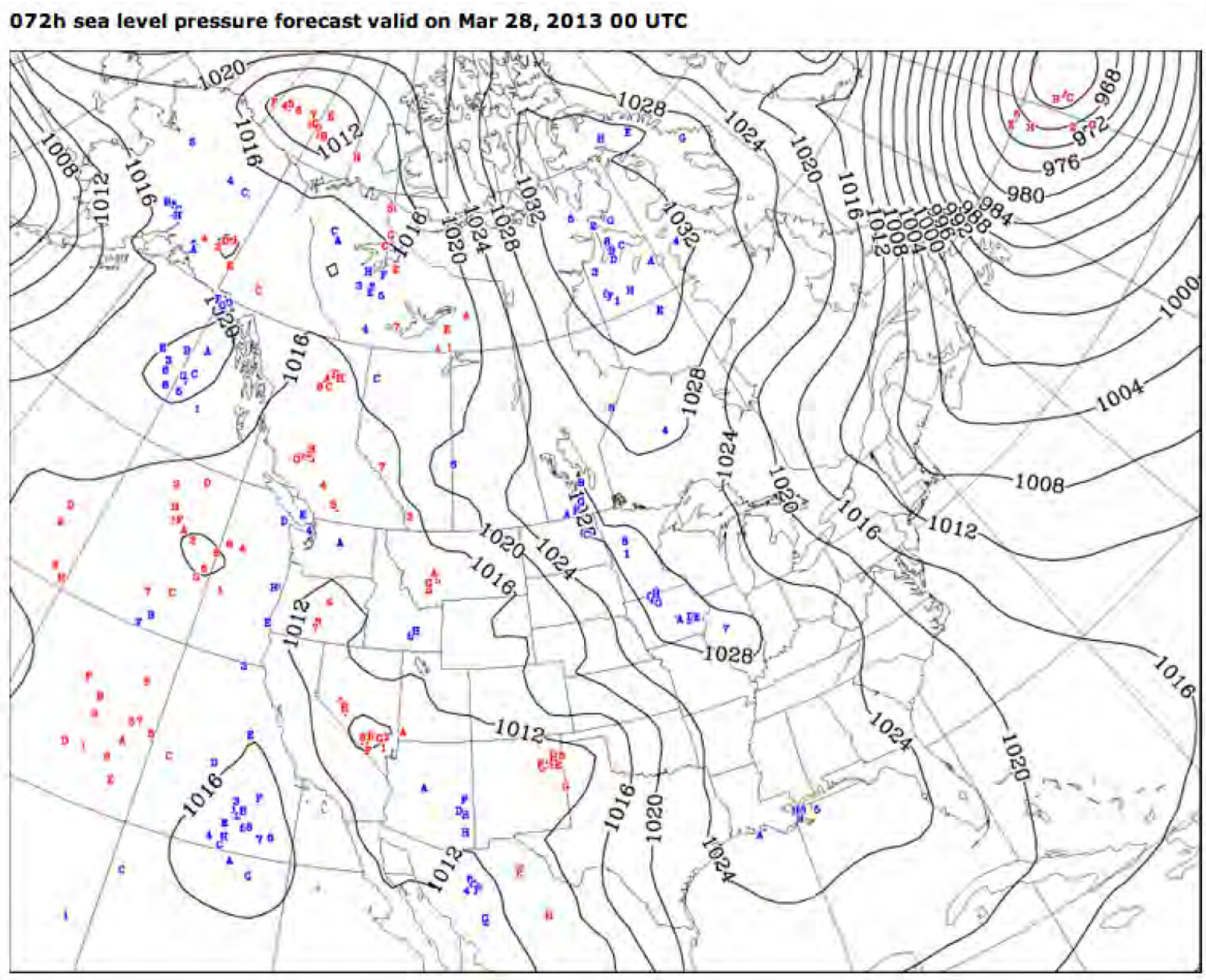




Separate zero from nonzero precip. members at UBC:

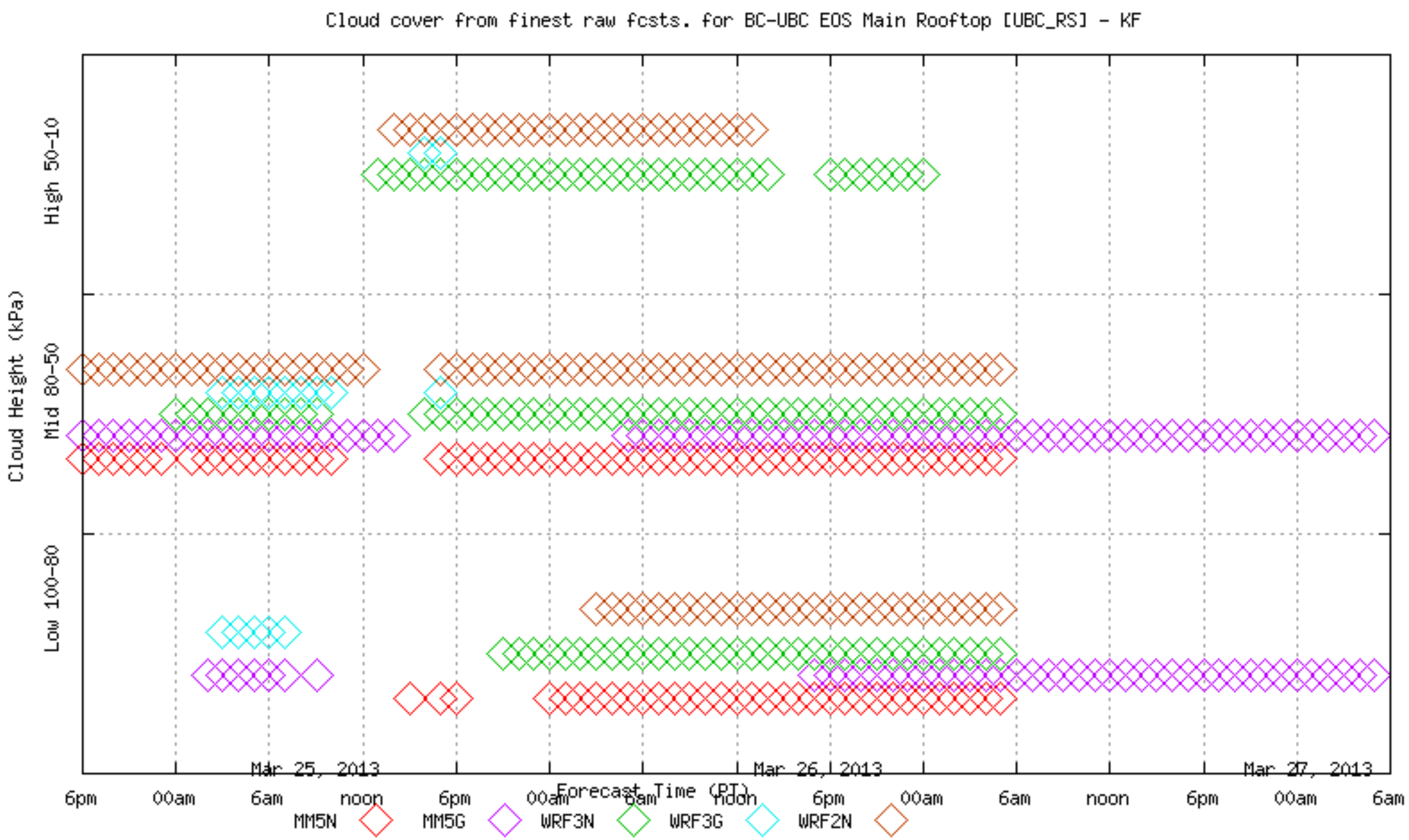


CMC: contours of ensemble average SLP, with red and blue showing center locations for Lows & Highs



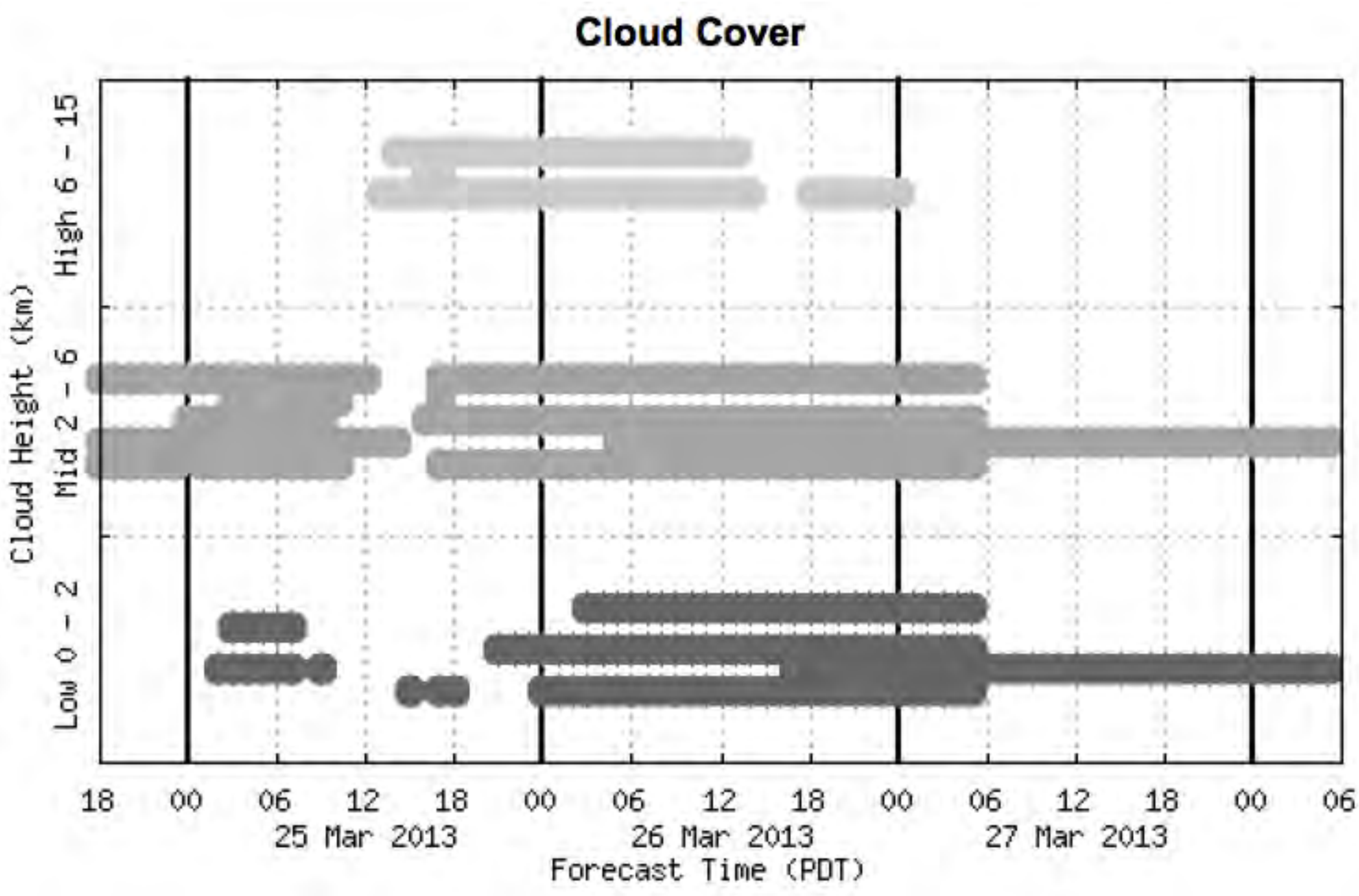
UBC Ensemble Cloud Cover:

version for meteorologists



UBC Ensemble Cloud Cover:

version for public



...for future lecture (originally presented by Dr. Thomas Nipen

- ensemble calibration / calibrated probabilistic forecasts
- other postprocessing of ensembles

Summary: Ensembles

- Role of ensembles in improving forecast skill for a nonlinear, chaotic system such as the atmosphere.
- Operational ensemble forecast methods.
- Deterministic ensemble forecasts (DEF).
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