NOAA-CIRES Climate Diagnostics Center

Advancing understanding and predictions of climate variability

Introduction to Numerical Weather Prediction and Ensemble Weather Forecasting

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NWP Process

Gather Observations

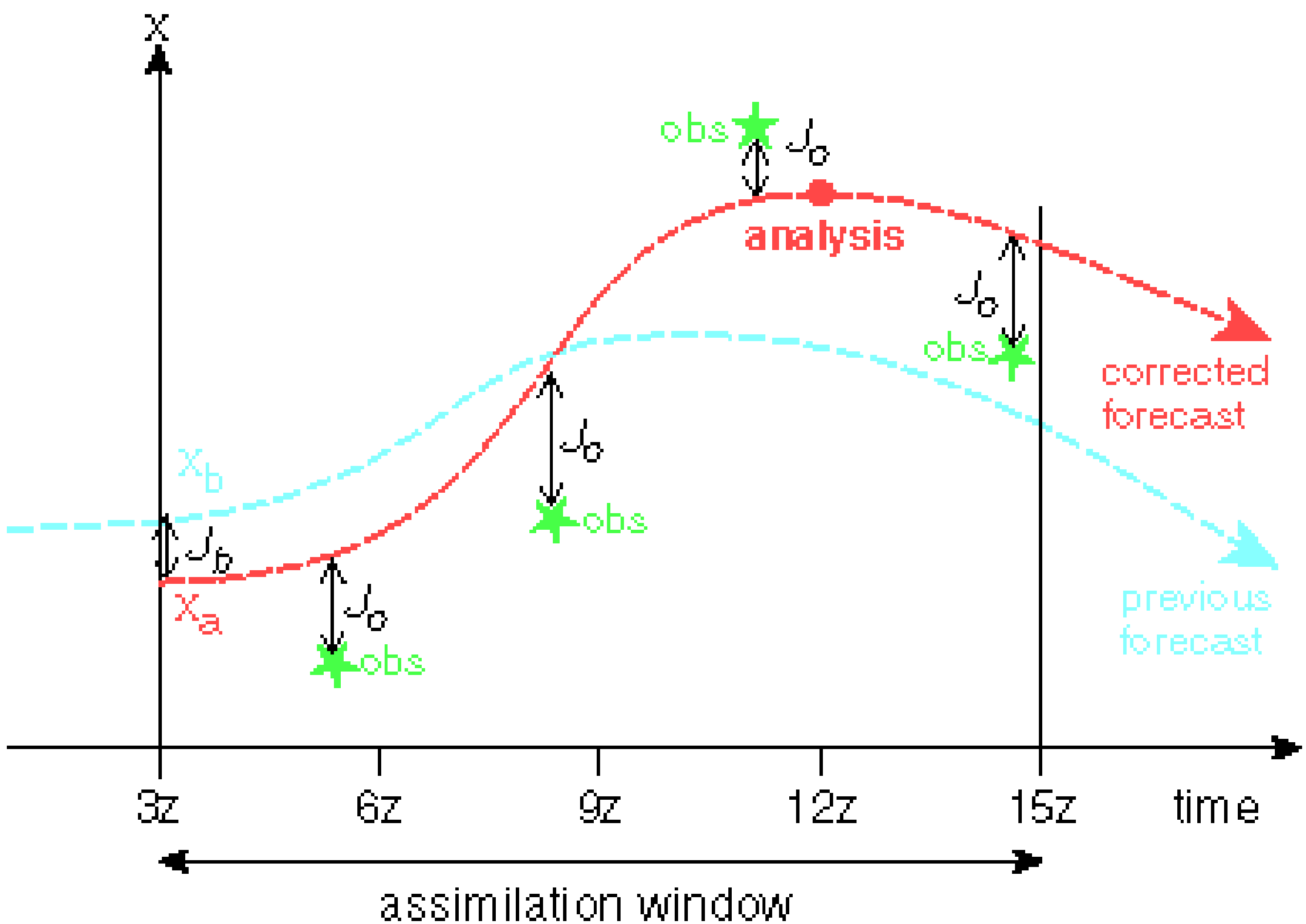
→ Data Assimilation

→ Numerical Weather Predictions

→ Forecast Postprocessing

→ Issue forecasts, Evaluate

Current state-of-the-art data assimilation: 4-dimensional variational assimilation (4D-Var)



Courtesy ECMWF

Equations of motion (ECWMF model)

$$\frac{\partial U}{\partial t} + \frac{1}{a\cos^2\theta}\left\{U\frac{\partial U}{\partial \lambda} + v\cos\theta\frac{\partial U}{\partial \theta}\right\} + \dot{\eta}\frac{\partial U}{\partial \eta}$$

East-west wind

$$(-fv) + \frac{1}{a}\left\{\frac{\partial \phi}{\partial \lambda} + R_{\mathrm{dry}}T_{\mathrm{v}}\frac{\partial}{\partial \lambda}(\ln p)\right\} = P_U + K_U$$

$$\frac{\partial V}{\partial t} + \frac{1}{a\cos^2\theta}\left\{U\frac{\partial V}{\partial \lambda} + V\cos\theta\frac{\partial V}{\partial \theta} + \sin\theta(U^2 + V^2)\right\} + \dot{\eta}\frac{\partial V}{\partial \eta}$$

North-south wind

$$+ fU + \frac{\cos\theta}{a}\left\{\frac{\partial \phi}{\partial \theta} + R_{\mathrm{dry}}T_{\mathrm{v}}\frac{\partial}{\partial \theta}(\ln p)\right\} = P_V + K_V$$

$$\frac{\partial T}{\partial t} + \frac{1}{a\cos^2\theta}\left\{U\frac{\partial T}{\partial \theta} + V\cos\theta\frac{\partial T}{\partial \theta}\right\} + \dot{\eta}\frac{\partial T}{\partial \eta} - \frac{\kappa T_{\mathrm{v}}\omega}{(1 + (\delta - 1)q)p} = P_T + K_T$$

Temperature

$$\frac{\partial q}{\partial t} = \frac{1}{a\cos^2\theta}\left\{U\frac{\partial q}{\partial \lambda} + V\cos\theta\frac{\partial q}{\partial \theta}\right\} = \eta\frac{\partial q}{\partial \eta} = P_q + K_q$$

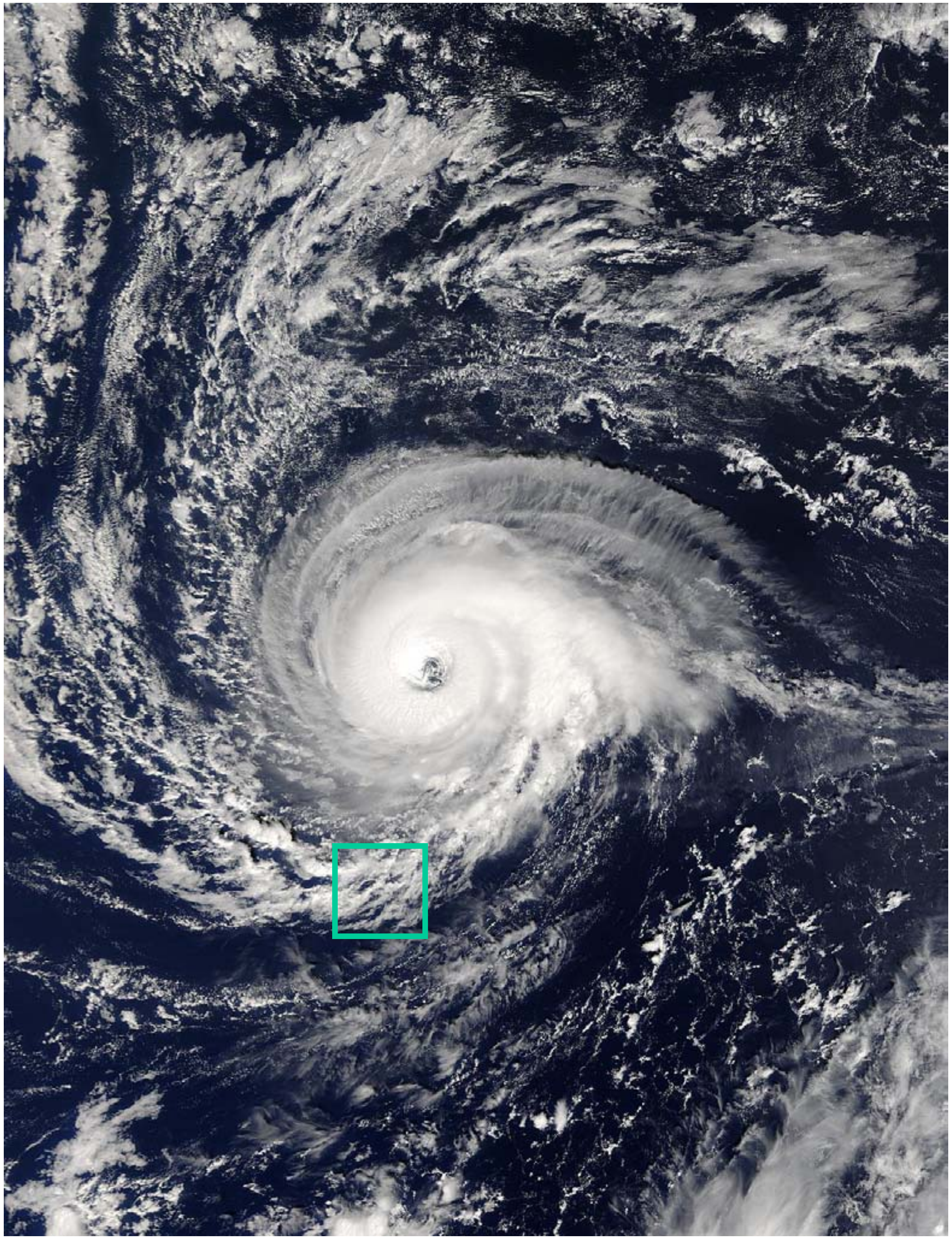
Humidity

$$\frac{\partial}{\partial t}\left(\frac{\partial p}{\partial \eta}\right) + \nabla.\left(\mathbf{v}_{\mathrm{H}}\frac{\partial p}{\partial \eta}\right) + \frac{\partial}{\partial \eta}\left(\dot{\eta}\frac{\partial p}{\partial \eta}\right) = 0$$

Continuity of mass

$$\frac{\partial p_{\mathrm{surf}}}{\partial t} = -\int_0^1 \nabla.\left(\mathbf{v}_{\mathrm{H}}\frac{\partial p}{\partial \eta}\right)d\eta$$

Surface pressure



Source: MODIS

"Parameterizations"

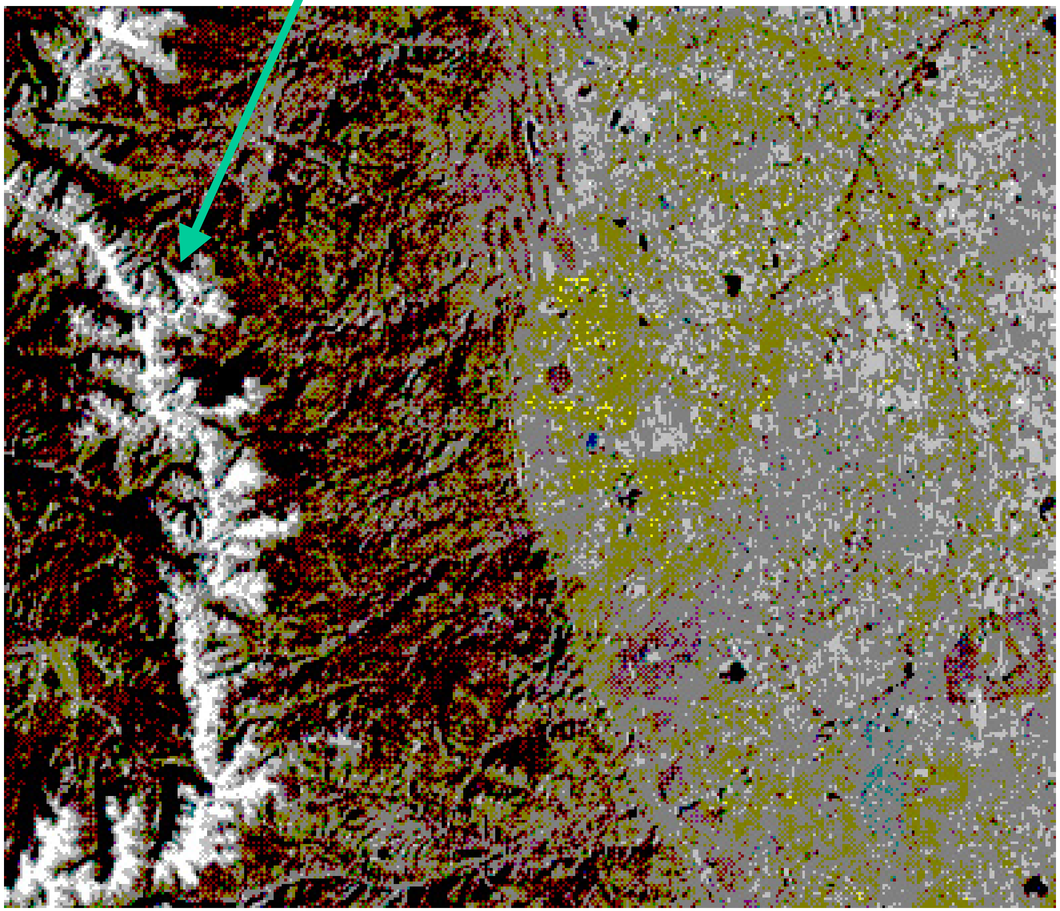
Much of the weather occurs at scales smaller than those resolved by the weather forecast model. Model must treat, or "parameterize" the effects of the sub-gridscale on the resolved scale.

Other parameterizations

- Land surface
- Cloud microphysics
- Turbulent diffusion and interactions with surface
- Orographic drag
- Radiative transfer

A lot happens inside a grid box

Rocky Mountains



Approximate size of one grid box in NCEP ensemble system

Denver

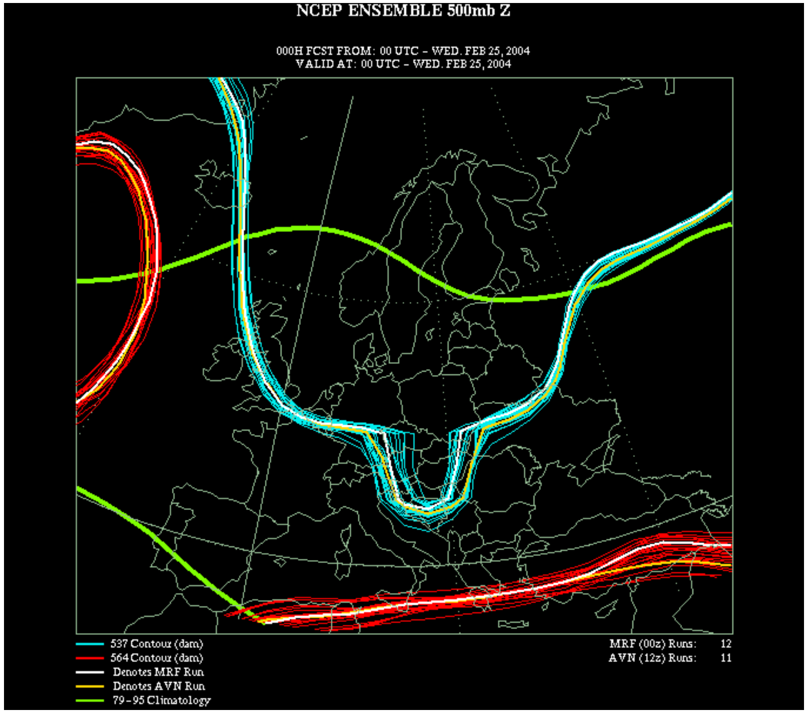
Source: accessmaps.com

Questions

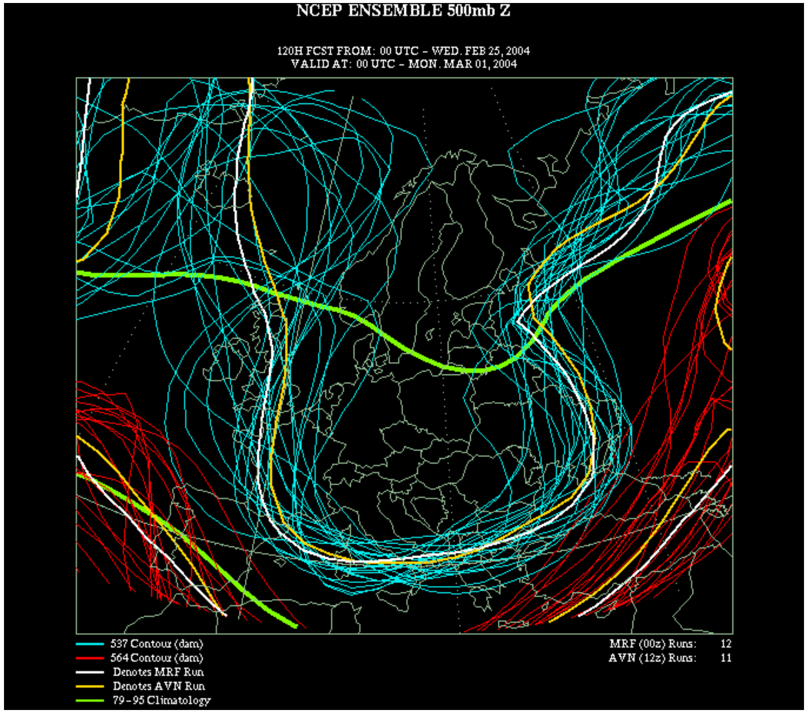
- Can we accurately forecast the evolution of the pdf of the grid-box average weather? (*focus mostly on this*)
- How do we downscale from a grid-box average to a particular river basin or sub-area?

Estimating the pdf of the weather: problem 1: chaos

Initial condition uncertainty

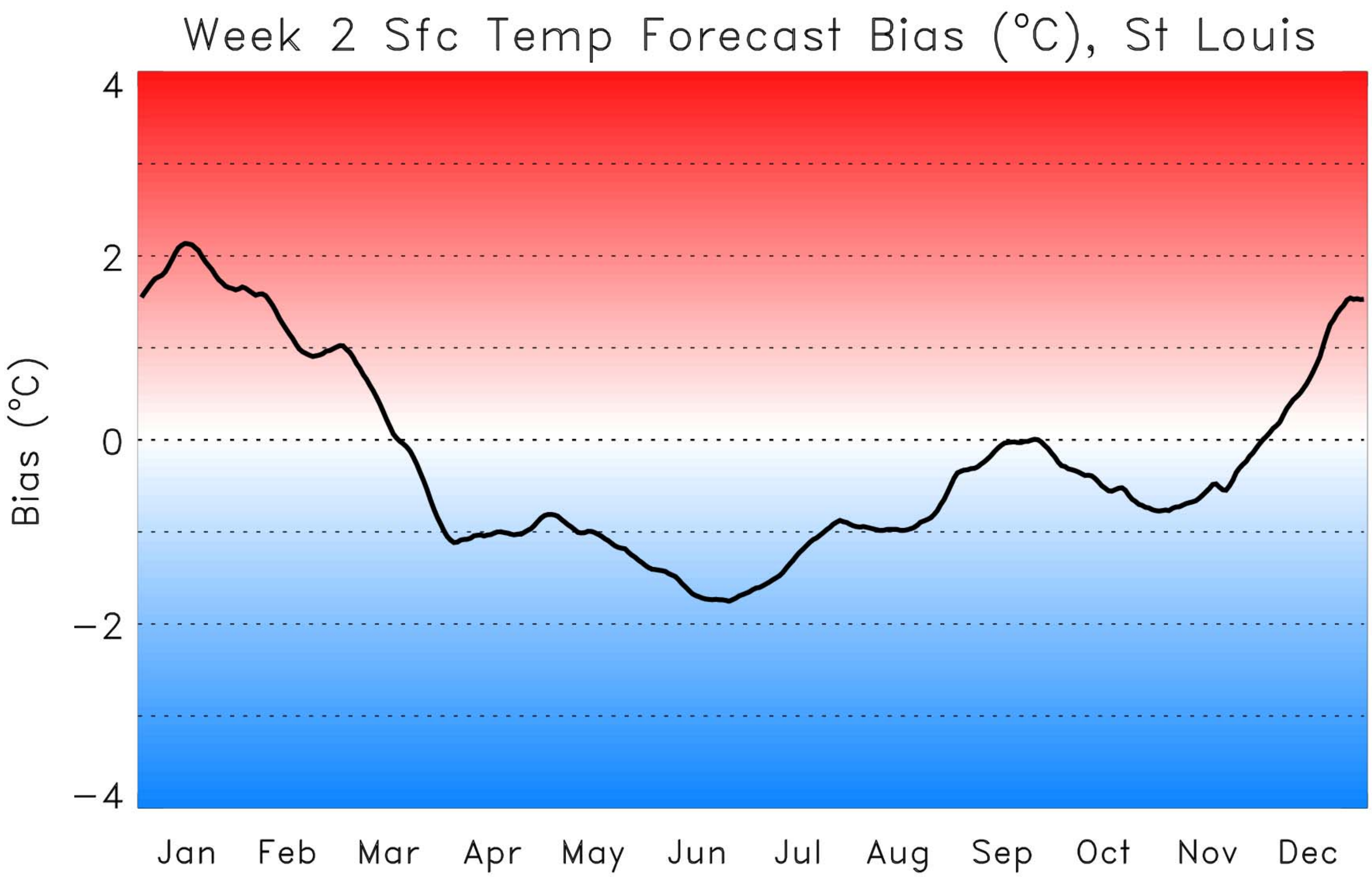


5-day forecast uncertainty



Problem 2: model error

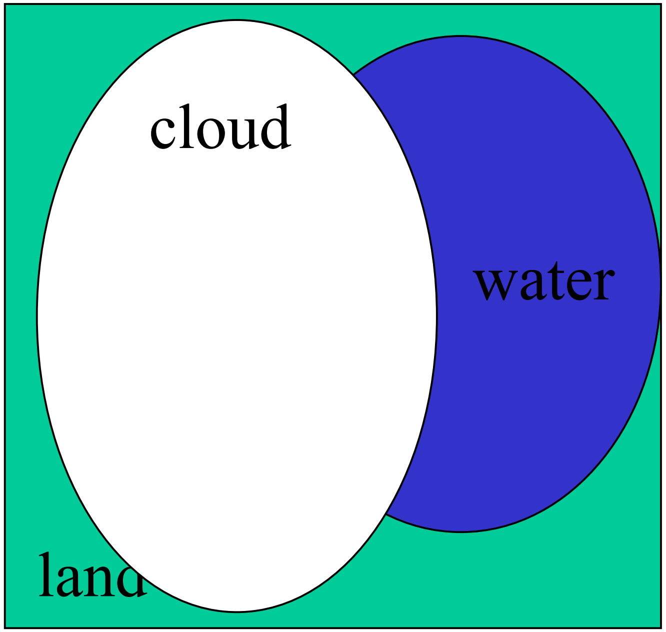
(here, systematic component)

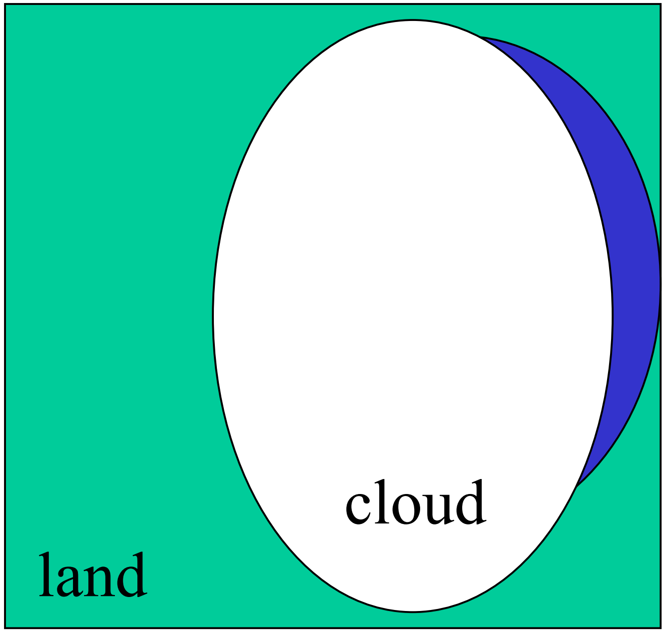


Problem 2: model error

(here, random component)

Envision a GCM grid box comprised of part land, part water. It is 40 % covered by cloud. The flux of sensible and latent heat from the surface averaged over the grid box will depend on where the cloud is positioned inside the grid box. The unknowable sub-gridscale detail thus contributes an element of randomness to the forcing at the scale of the grid box.

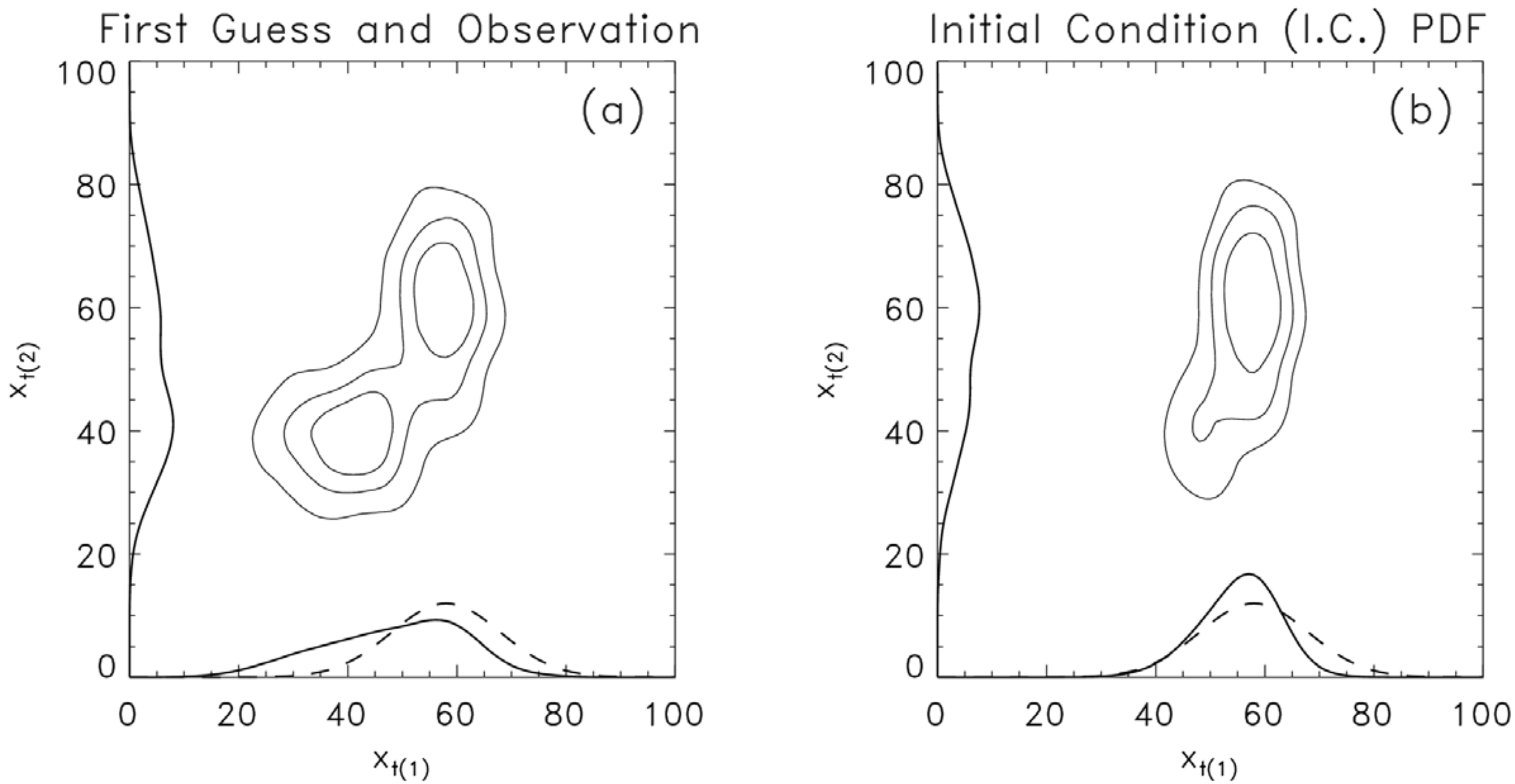




Probabilistic numerical weather prediction: theory

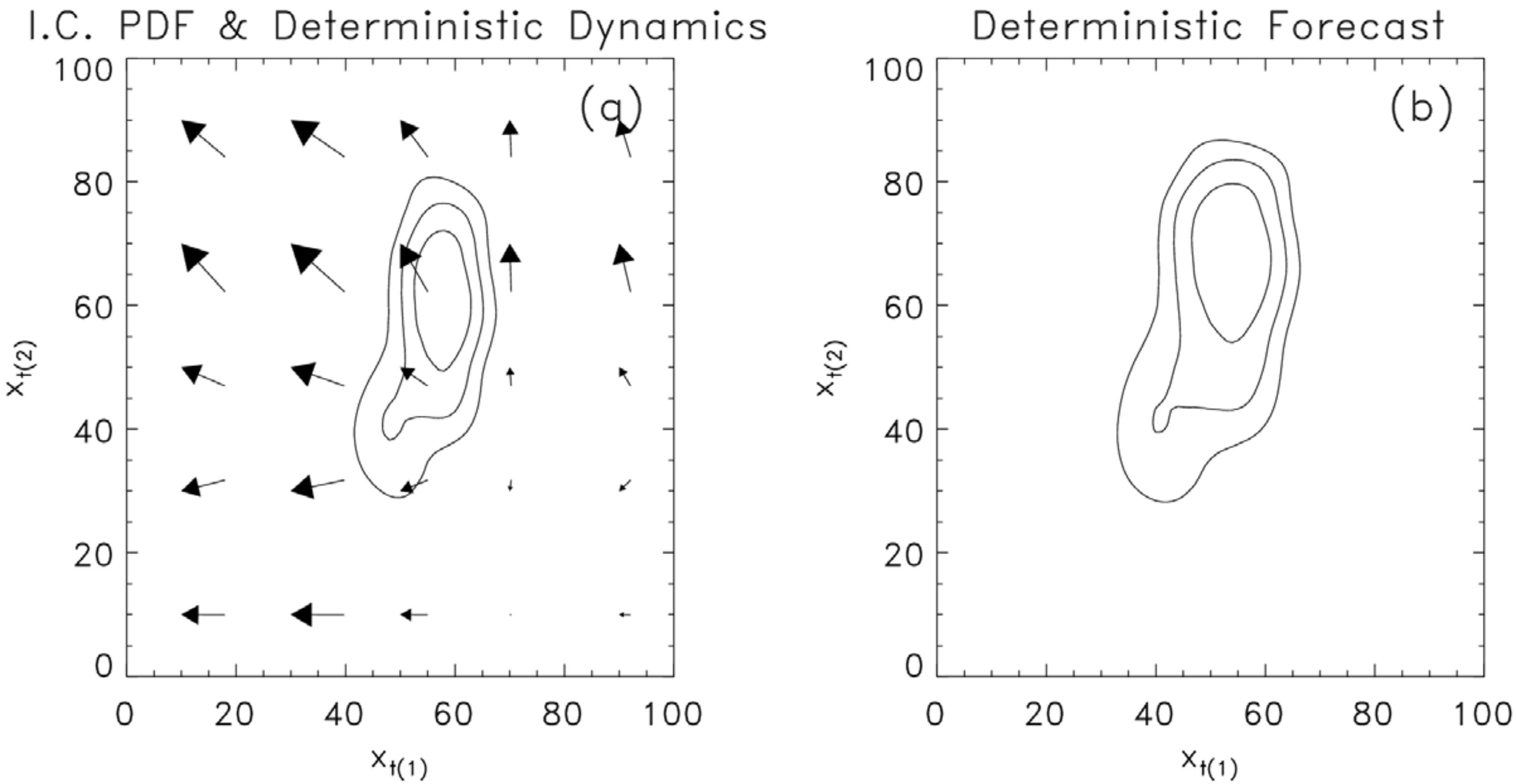
- Assume prior pdf of model state
- Step 1: assimilate new observations to sharpen pdf
- Step 2: forecast pdf forward in time
- Cycle short-range forecasts back to step 1.

Probabilistic NWP: data assimilation



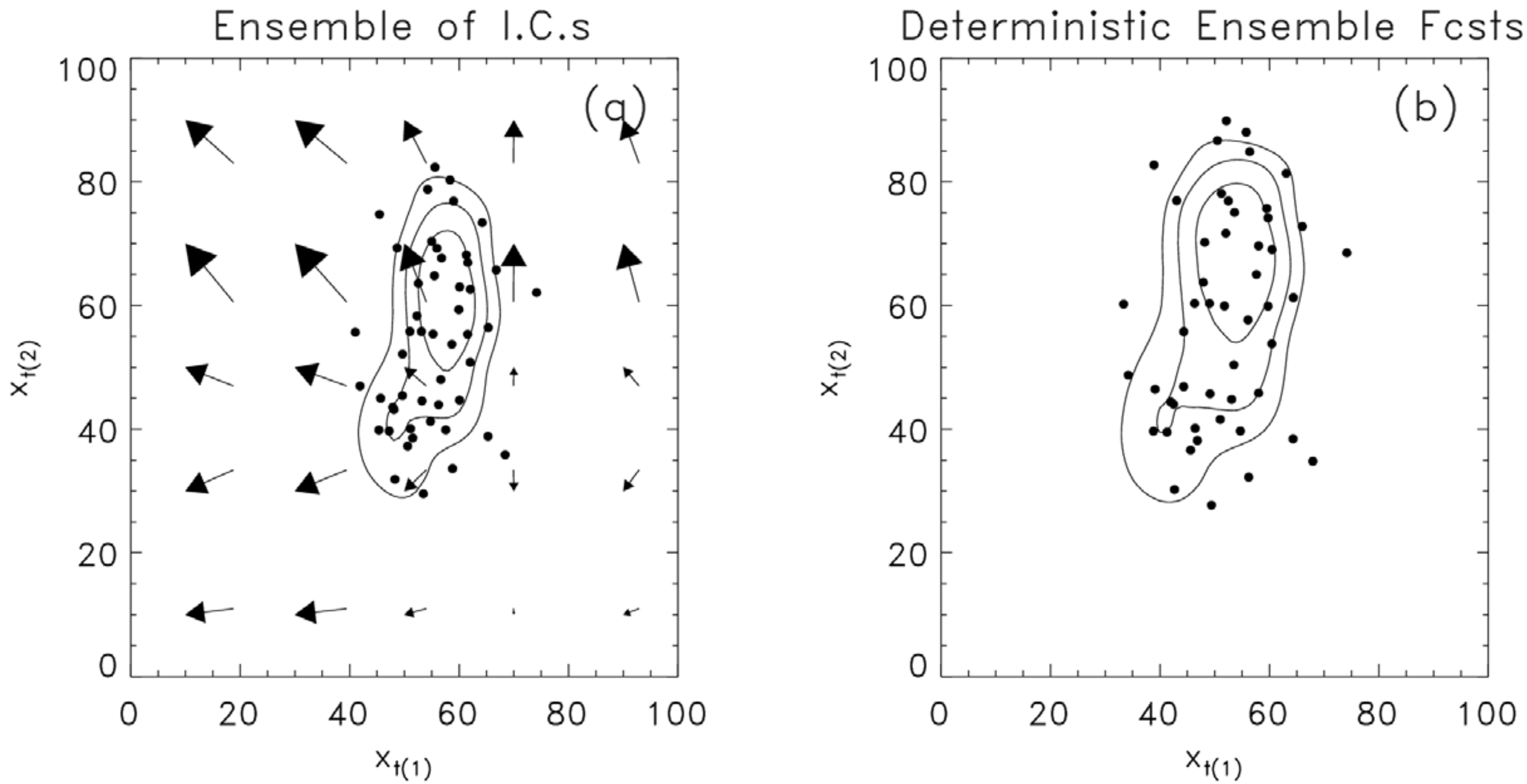
Envision a prior estimate of a two-dimensional model state assimilating a new observation (which measures only 1st component of the state.

Probabilistic NWP: forecasting pdf with perfect model



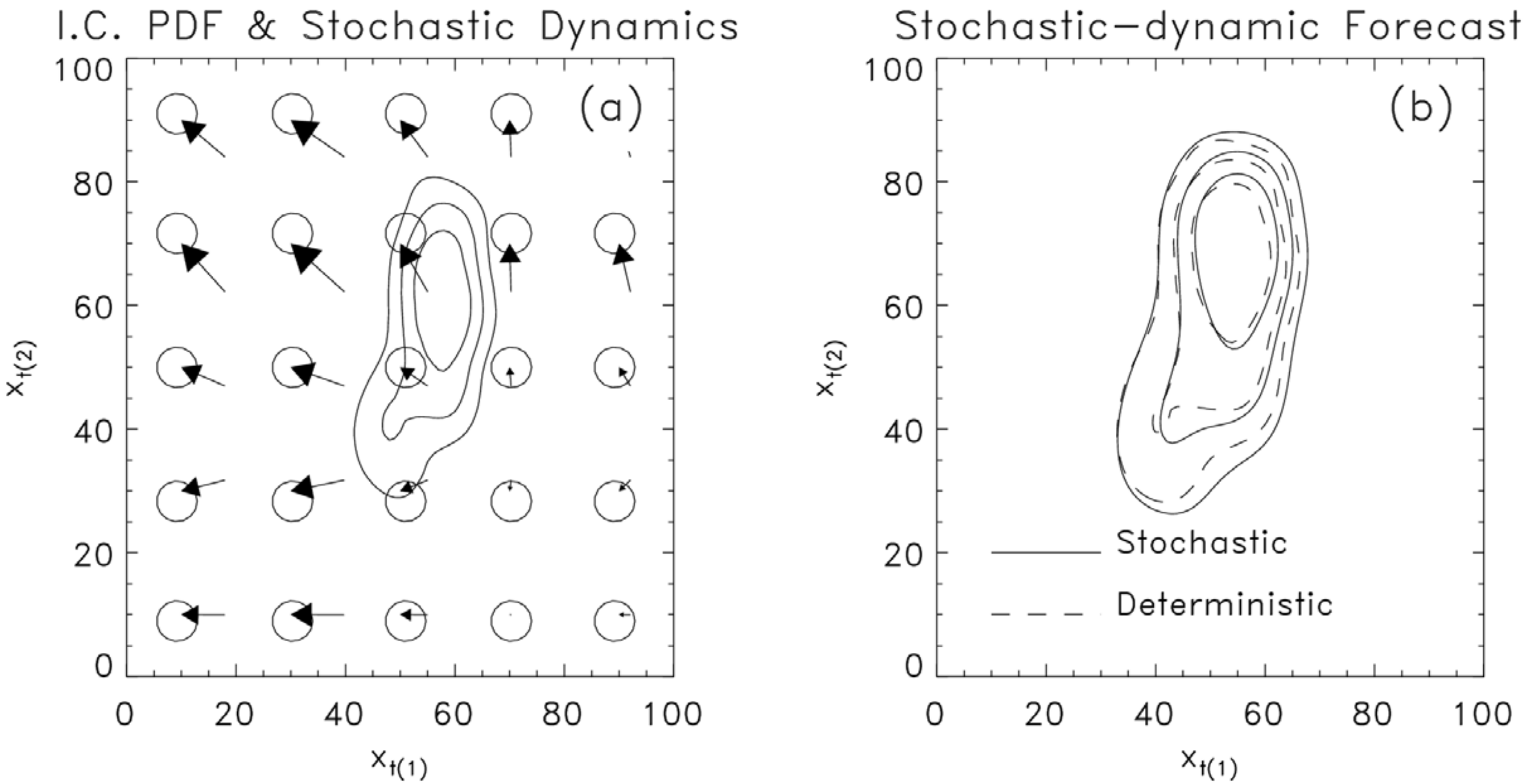
Arrows indicate state-dependent deterministic forecast dynamics, which tend to smear out probabilities with increasing time.

Probabilistic NWP: approximating with deterministic ensemble forecasts



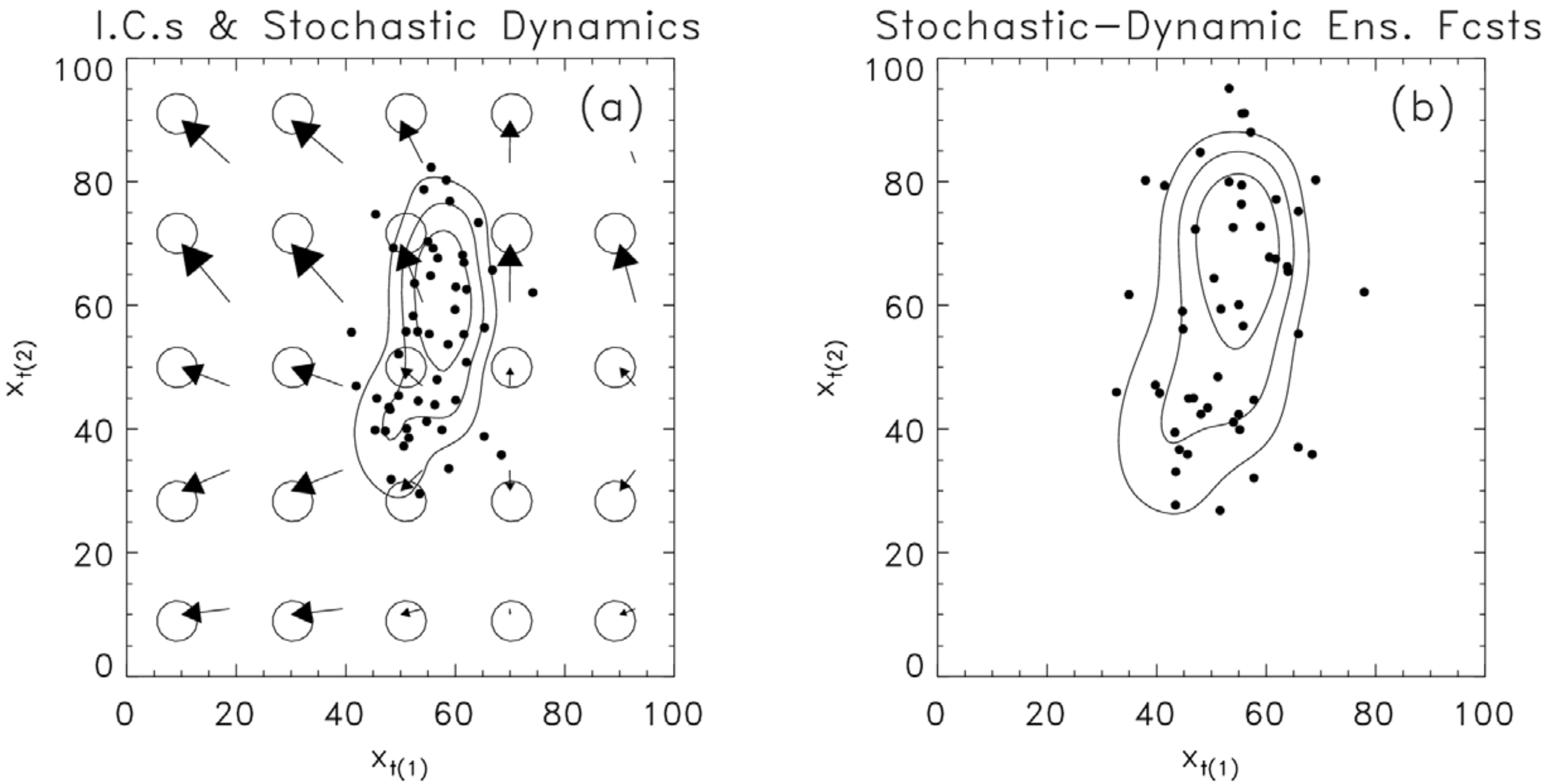
Generate samples from initial pdf. Propagate each sample forward in time using deterministic forecast model dynamics. Get random sample of pdf propagated through Liouville eqn.

Probabilistic NWP: forecasting pdf with imperfect model



In reality, it's more appropriate to think of forecast model as part deterministic (arrows) plus part stochastic (circles). Stochastic part may include state-dependent bias correction that shifts pdf and addition of random error that diffuses pdf.

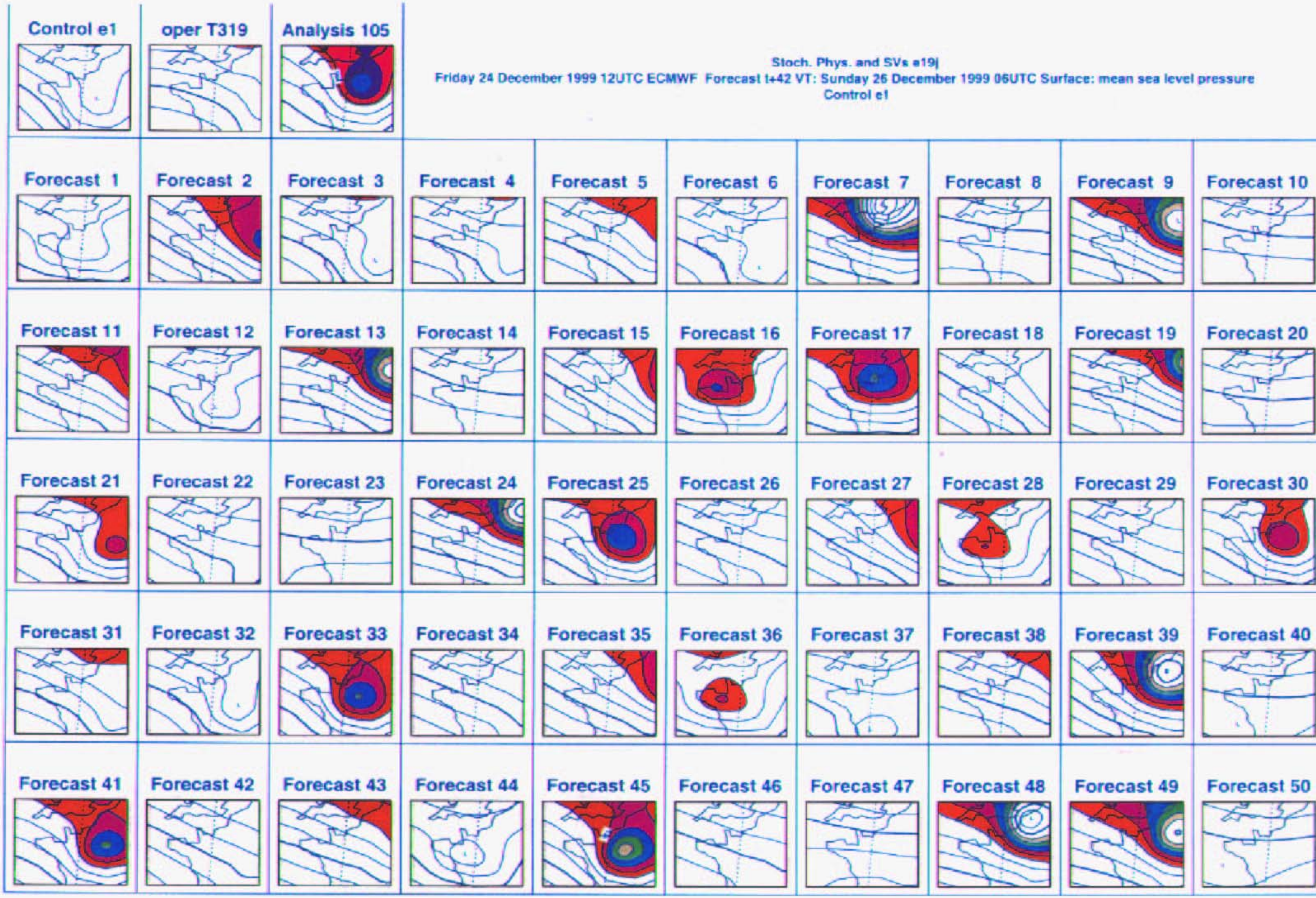
Probabilistic NWP: approximating with stochastic ensemble forecasts



Generate samples from initial pdf. Propagate each sample forward in time using stochastic-dynamic forecast model. Should get random sample of pdf propagated through Fokker-Planck eqn.

Ensemble forecasts: where are we today?

- Generating initial conditions: Each center has adopted their own approximate way of sampling from initial condition pdf.
  - Breeding (NCEP)
  - Singular vector (ECMWF)
  - Perturbed observation (Canada)
- Stochastic-dynamic ensemble work just beginning (e.g., Buizza et al. 1999)
- Many attempts to post-process ensemble forecasts to provide reliable probability forecasts.



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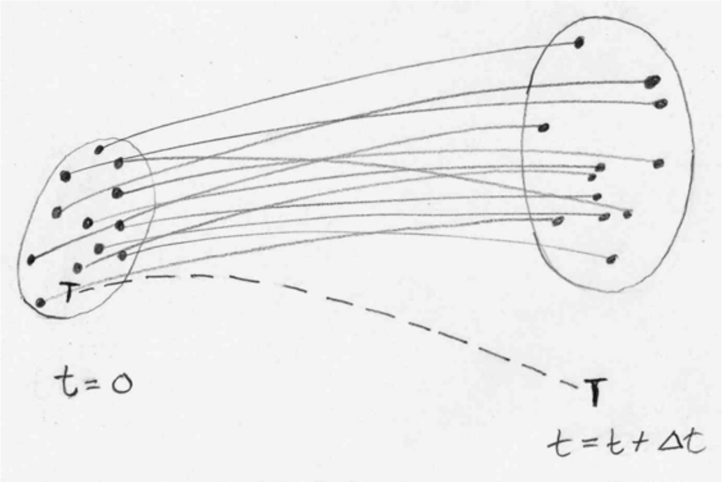
Typical problems with current generation ensemble forecasts

- Would like to maximize pdf sharpness subject to calibration. But:



- Ensemble forecasts are biased
  - Ensemble mean different (systematic model error; improve the model or post-process to correct errors)
  - Ensemble spread less than it ought to be (better initial conditions, higher-res forecasts, incorporating stochastic effects).

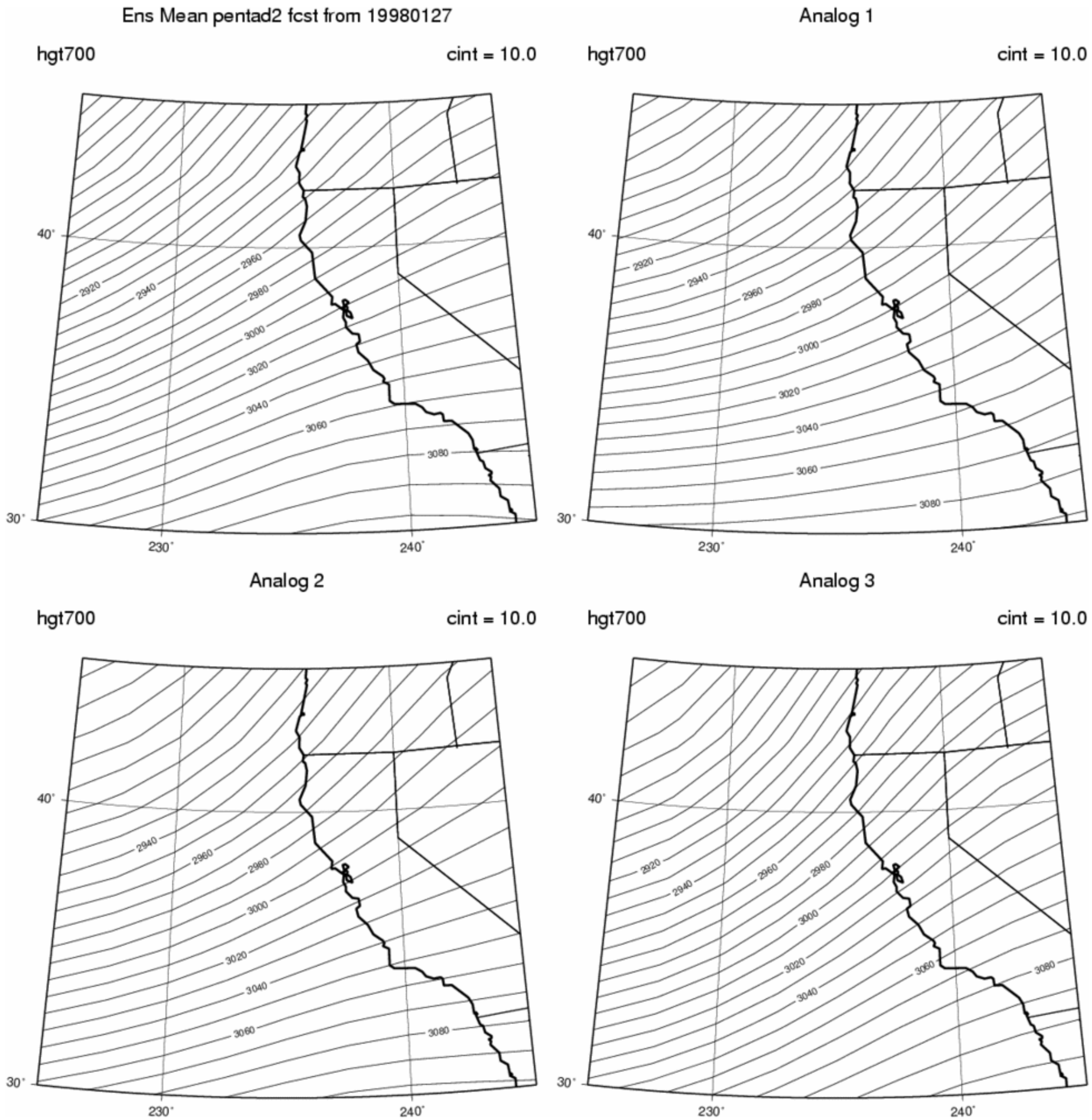
Downscaling

- Even if NWP centers produce calibrated ensemble forecasts at grid scale, much of the important weather for hydrology happens at the sub-gridscale.
- Ways to downscale will be a common topic during this workshop
- One possibility: find analogs from the past; use actual weather observations from these analogs.

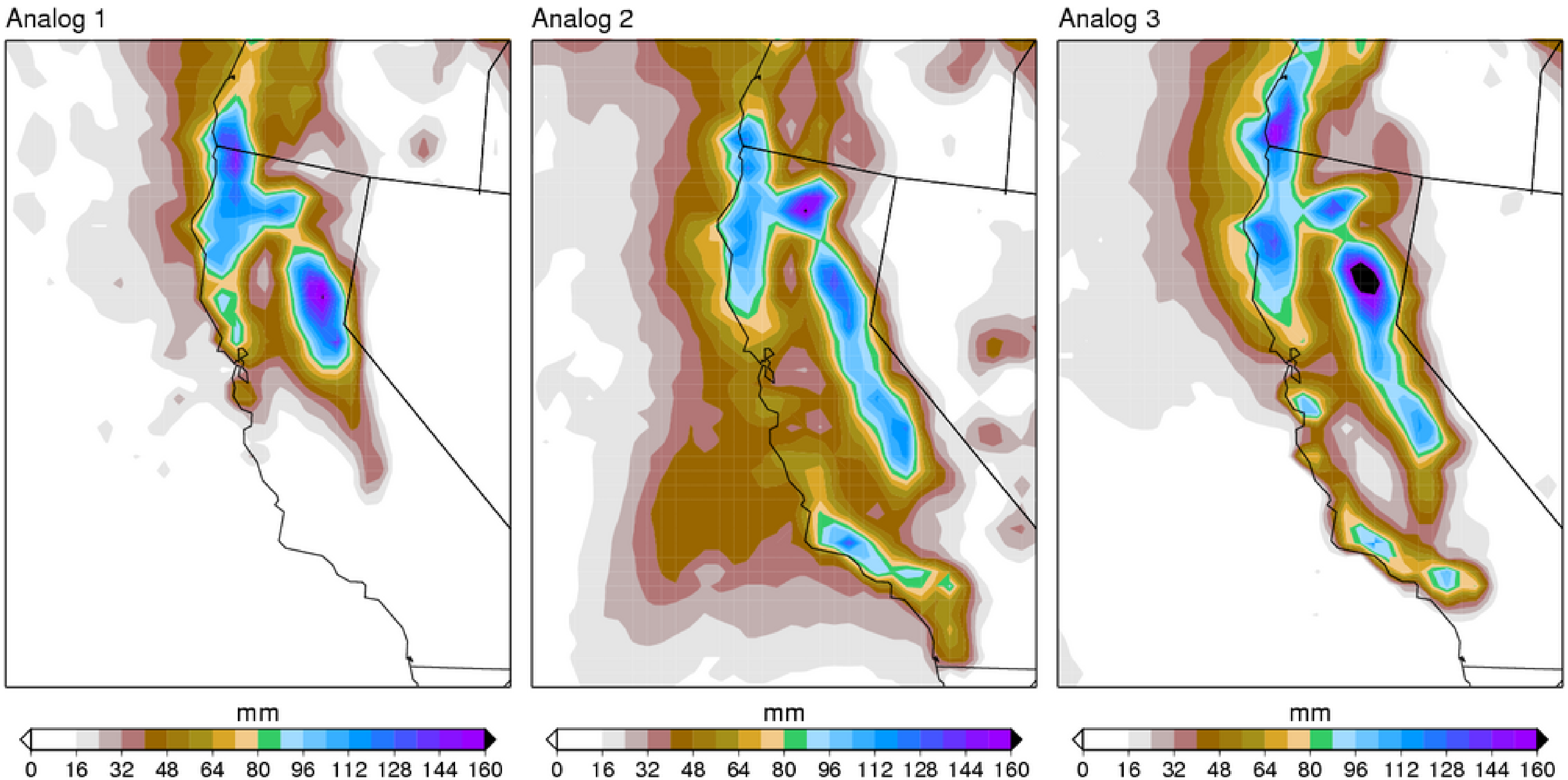
Example of downscaling

- Experimental re-forecast project with low-resolution version of ECMWF model (www.cdc.noaa.gov/~jsw/refcst)
- 23 years of 2-week bred ensemble forecasts centered on reanalysis initial condition
- Compute ensemble mean forecast, find days in past where past forecast resembled current forecast (in a limited area)
- Pluck out actual weather data for each of those days
- Use that weather to drive streamflow applications.

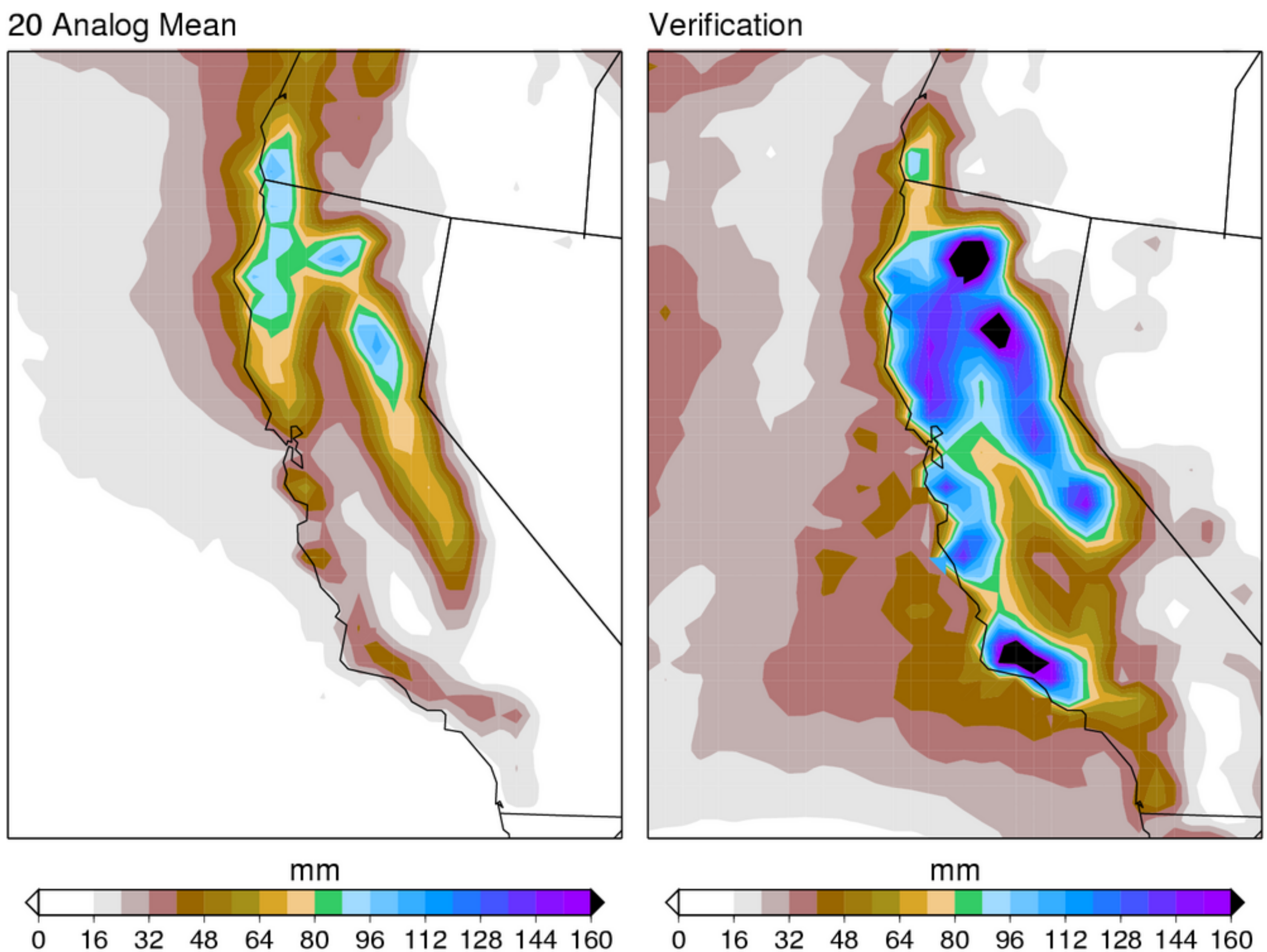
Example: 5-day forecast and analogs



Example: 5-day forecast and analogs



Example: 5-day forecast and analogs



Conclusions

- Ensemble forecast technology maturing; better probabilistic forecasts with each passing year
- Still can’t expect raw ensemble data to provide reliable weather input to drive streamflow models without some adjustment
- How do we best couple weather and streamflow ensembles? Not sure…let’s talk.