

# Data Assimilation Introit

Brian J. Etherton  
University of North Carolina

# The next 90 minutes of your life

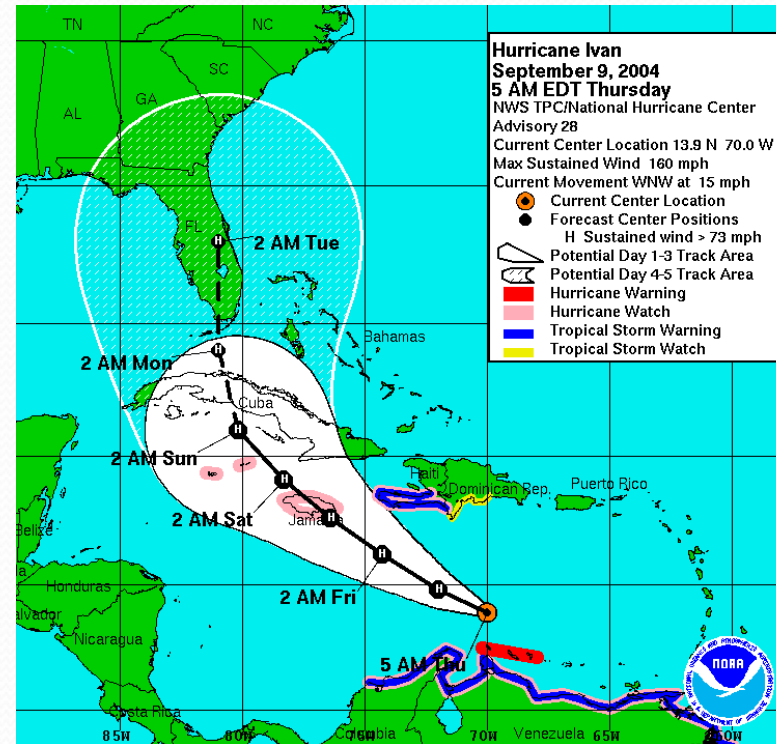
- Data Assimilation Introit
- Different methodologies
- Barnes Analysis in IDV





# NWP Error Sources

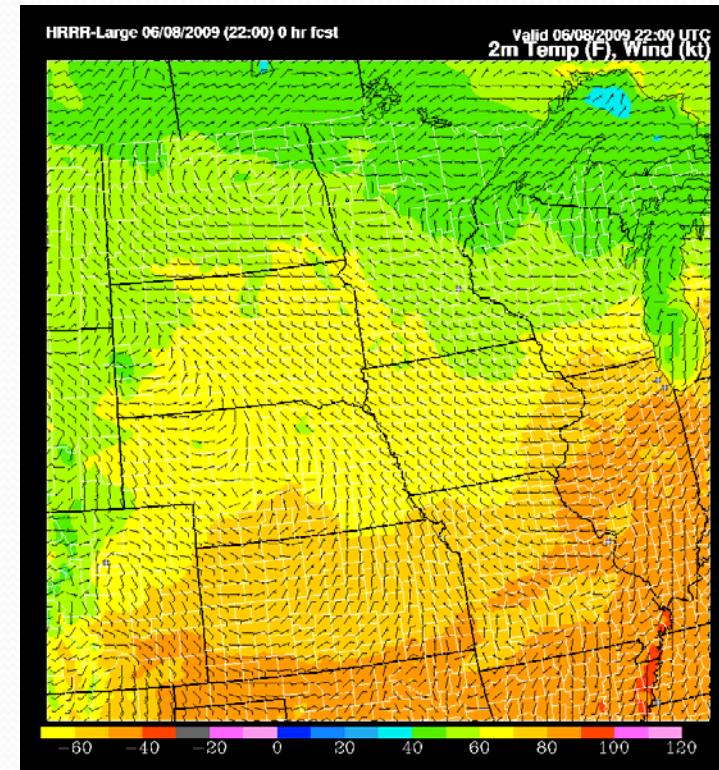
1. Intrinsic Predictability Limitations
  - a) Is the system inherently chaotic?
2. Errors in the Model
  - a) Does the model represent the system correctly?
  - b) Is model resolution sufficient?
  - c) Are unresolved physical processes well parameterized?
3. Errors in the Initial Conditions and Boundary Conditions





# Data Assimilation Introit

- Data assimilation is the procedure of getting the information content of observations into the numerical modeling system.
- The output of data assimilation is a maximum likelihood (optimal) estimate of the atmosphere, called an analysis, which can be used as the initial conditions for a numerical model.





# Data Assimilation Introit

- Optimal analysis of the atmosphere obtained by combining a model forecast (first guess / background field) with observations.
- Some issues to attend to with data:
  - Data can be anything, and sometimes can be parameters that are not the fundamental state variables of the governing equations (radiance, for example)
  - Data can be of varying quality (instrument error, error of representation) – observations are not perfect
  - Data coverage may not be complete (500mb temperature over Cheyenne, WY, no sonde site) – need first guess

# Data Assimilation Introit

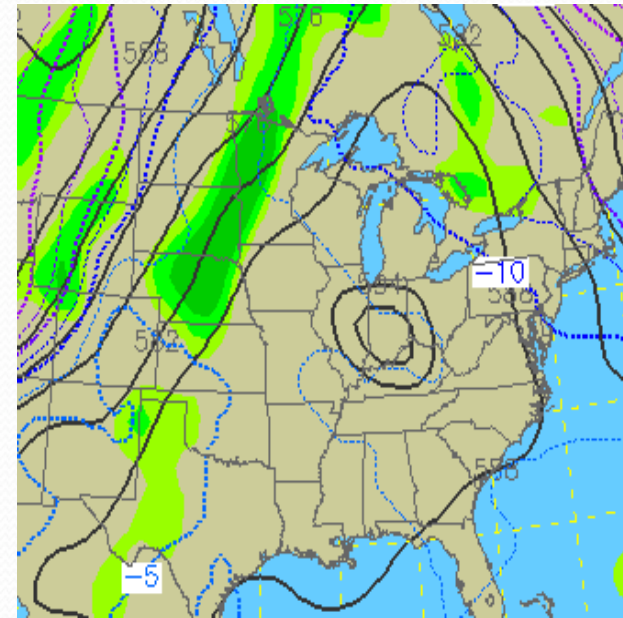
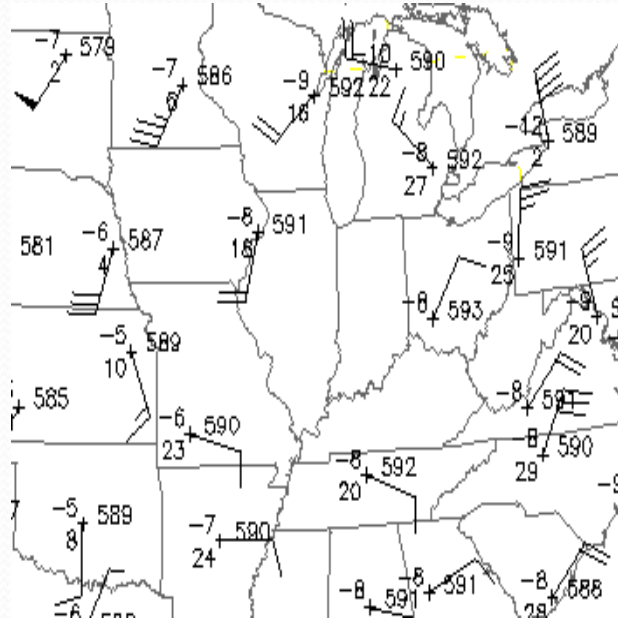
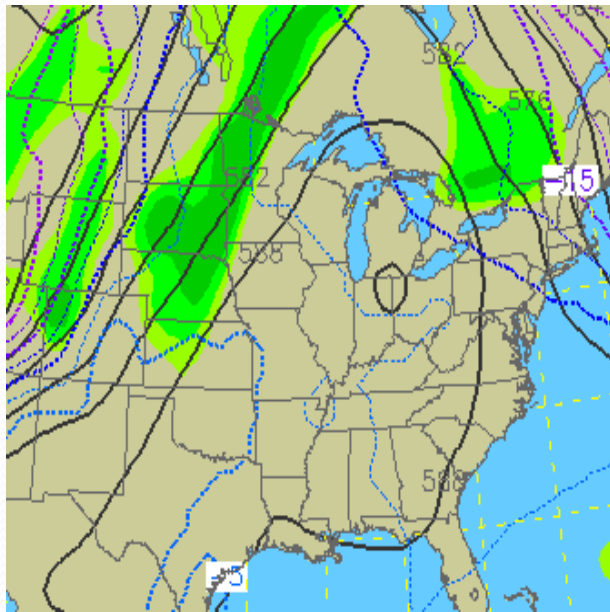
- Optimal analysis of the atmosphere obtained by combining a model forecast (first guess / background field) with observations.
- The first guess field / background field is usually a short-range forecast from the previous analysis cycle
  - The first guess at 1200 UTC could be the 6-hour forecast from the 0600 UTC model
- First guess field provides all state variables (T, p, q, etc.) at all grid point locations.
- First guess needs to be moved closer to observed values (it's just a guess, after all).



# Data Assimilation Introit

- Optimal analysis of the atmosphere obtained by combining a model forecast (first guess / background field) with observations.
- Some issues with this:
  - Observational data is irregular in space and time
  - Model data is on a grid at regular times
  - Perfect fit to data – might get spurious results in model
  - Perfect fit to model – might be missing / under-representing important features
- Great to get the best of both the obs and first guess

# Data Assimilation Introit



First Guess + Observations = Analysis

How does one optimally combine the first guess field and the observations?



# Data Assimilation – One Value

- Consider two estimates of the temperature in this room.
  - $T_F$  shall be what we set the thermostat to (a forecast)
  - $T_O$  shall be the value from Mohan's watch (an observation)
- Use average squared errors (Variance) to weight the two estimates
  - Where  $\sigma_O^2$  = Error Variance associated with  $T_O$
  - Where  $\sigma_F^2$  = Error Variance associated with  $T_F$
- The optimal estimate (most likely value) of the temperature in the room, ( $T_A$ ), is:

$$T_A - T_F = (\sigma_F^2)(\sigma_F^2 + \sigma_O^2)^{-1}[T_O - T_F]$$

# Data Assimilation – One Value

- The estimate of the temperature with minimum error variance, the analysis value ( $T_A$ ), is:

$$T_A - T_F = (\sigma_F^2)(\sigma_F^2 + \sigma_O^2)^{-1}[T_O - T_F]$$

- What if the thermostat is perfect?
  - Then  $\sigma_F^2 = 0$
  - Then  $T_A - T_F = 0$ , so  $T_A = T_F$
- What if Mohan's watch is perfect?
  - Then  $\sigma_O^2 = 0$
  - Then  $T_A - T_F = T_O - T_F$ , so  $T_A = T_O$
- $T_A$  is a weighted average of the observation and first guess



# Data Assimilation – Full model

$$\mathbf{T}_A - \mathbf{T}_F = (\sigma_F^2)(\sigma_F^2 + \sigma_O^2)^{-1}[\mathbf{T}_O - \mathbf{T}_F]$$

Assuming that observation and forecast errors are uncorrelated, the analysis increment ( $\mathbf{x}^a - \mathbf{x}^f$ ) that minimizes analysis error variance is (Cohn, 1997):

$$\underline{\mathbf{x}}^a - \underline{\mathbf{x}}^f = \underline{\mathbf{B}}\underline{\mathbf{H}}^T(\underline{\mathbf{H}}\underline{\mathbf{B}}\underline{\mathbf{H}}^T + \underline{\mathbf{R}})^{-1}[\underline{\mathbf{y}} - \underline{\mathbf{H}}\underline{\mathbf{x}}^f]$$

# Analysis equation

$$\mathbf{T}_A - \mathbf{T}_F = (\sigma_F^2)(\sigma_F^2 + \sigma_O^2)^{-1}[\mathbf{T}_O - \mathbf{T}_F]$$

$$\underline{\mathbf{x}}^a - \underline{\mathbf{x}}^f = \underline{\mathbf{B}}\underline{\mathbf{H}}^T(\underline{\mathbf{H}}\underline{\mathbf{B}}\underline{\mathbf{H}}^T + \underline{\mathbf{R}})^{-1}[\underline{\mathbf{y}} - \underline{\mathbf{H}}\underline{\mathbf{x}}^f]$$

Model State Vector ( $\underline{\mathbf{x}}^a, \underline{\mathbf{x}}^f$ )

- A vector with all model variables at all model gridpoints

Observation Vector ( $\underline{\mathbf{y}}$ )

- A vector equal with all observations

Observation Operator ( $\underline{\mathbf{H}}$ )

- Converts data from observation space into model space (spatial conversion, variable conversion)



# Analysis equation

$$\mathbf{T}_A - \mathbf{T}_F = (\sigma_F^2)(\sigma_F^2 + \sigma_O^2)^{-1}[\mathbf{T}_O - \mathbf{T}_F]$$

$$\underline{\mathbf{x}}^a - \underline{\mathbf{x}}^f = \underline{\mathbf{B}}\underline{\mathbf{H}}^T(\underline{\mathbf{H}}\underline{\mathbf{B}}\underline{\mathbf{H}}^T + \underline{\mathbf{R}})^{-1}[\underline{\mathbf{y}} - \underline{\mathbf{H}}\underline{\mathbf{x}}^f]$$

Analysis Increment ( $\underline{\mathbf{x}}^a - \underline{\mathbf{x}}^f$ )

- A vector equal to the difference between the analysis and the first guess field.

Innovation Vector ( $\underline{\mathbf{y}} - \underline{\mathbf{H}}\underline{\mathbf{x}}^f$ )

- A vector equal to the difference between the observations and the first guess field, in observation space

# Analysis equation

$$\mathbf{T}_A - \mathbf{T}_F = (\sigma_F^2)(\sigma_F^2 + \sigma_O^2)^{-1}[\mathbf{T}_O - \mathbf{T}_F]$$
$$\underline{\mathbf{x}}^a - \underline{\mathbf{x}}^f = \underline{\mathbf{B}}\underline{\mathbf{H}}^T(\underline{\mathbf{H}}\underline{\mathbf{B}}\underline{\mathbf{H}}^T + \underline{\mathbf{R}})^{-1}[\underline{\mathbf{y}} - \underline{\mathbf{H}}\underline{\mathbf{x}}^f]$$

Observation error covariance matrix ( $\mathbf{R}$ )

- A matrix describing how errors of one observed parameter at one observing site correlate to errors of all observations (including itself)

First guess/Background error covariance matrix ( $\mathbf{B}$ )

- A matrix describing how errors of one parameter at one gridpoint correlate to errors of all parameters at all gridpoints (including itself)



# Analysis equation

$$\underline{\mathbf{x}}^a - \underline{\mathbf{x}}^f = \underline{\mathbf{B}}\underline{\mathbf{H}}^T(\underline{\mathbf{H}}\underline{\mathbf{B}}\underline{\mathbf{H}}^T + \underline{\mathbf{R}})^{-1}[\underline{\mathbf{y}} - \underline{\mathbf{H}}\underline{\mathbf{x}}^f]$$

Depending how you make B, this equation can be used for ‘optimal interpolation’, or the ‘Kalman Filter’.

Data Assimilation Analogy: driving with your eyes closed: open eyes every analysis time and correct trajectory

# Variational Schemes

$$\mathbf{T}_A - \mathbf{T}_F = (\sigma_F^2)(\sigma_F^2 + \sigma_O^2)^{-1}[\mathbf{T}_O - \mathbf{T}_F]$$

Multiplying both sides by  $(\sigma_F^2 + \sigma_O^2)$ , gives:

$$(\sigma_F^2 + \sigma_O^2)[\mathbf{T}_A - \mathbf{T}_F] = (\sigma_F^2)[\mathbf{T}_O - \mathbf{T}_F]$$

Expand out left hand side:

$$[\mathbf{T}_A - \mathbf{T}_F](\sigma_F^2) + [\mathbf{T}_A - \mathbf{T}_F](\sigma_O^2) = [\mathbf{T}_O - \mathbf{T}_F](\sigma_F^2)$$

Combining:

$$[\mathbf{T}_A - \mathbf{T}_F](\sigma_O^2) = [\mathbf{T}_O - \mathbf{T}_F](\sigma_F^2) - [\mathbf{T}_A - \mathbf{T}_F](\sigma_F^2) = [\mathbf{T}_O - \mathbf{T}_A](\sigma_F^2)$$

Divide all by  $(\sigma_F^2 \sigma_O^2)$ :

$$[\mathbf{T}_A - \mathbf{T}_F](\sigma_F^2)^{-1} = [\mathbf{T}_O - \mathbf{T}_A](\sigma_O^2)^{-1}$$

Minimize a cost-function:

$$J(\underline{\mathbf{x}}^a) = (1/2)[(\underline{\mathbf{x}}^a - \underline{\mathbf{x}}^f)\underline{\mathbf{B}}^{-1}(\underline{\mathbf{x}}^a - \underline{\mathbf{x}}^f)] + (1/2)[(\underline{\mathbf{y}} - \underline{\mathbf{H}}\underline{\mathbf{x}}^a)\underline{\mathbf{R}}^{-1}(\underline{\mathbf{y}} - \underline{\mathbf{H}}\underline{\mathbf{x}}^a)]$$



# Variational Schemes

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$$J(\underline{\mathbf{x}}^a) = (1/2)[(\underline{\mathbf{x}}^a - \underline{\mathbf{x}}^f) \underline{\mathbf{B}}^{-1}(\underline{\mathbf{x}}^a - \underline{\mathbf{x}}^f)] + (1/2)[(\underline{\mathbf{y}} - \underline{\mathbf{H}}\underline{\mathbf{x}}^a) \underline{\mathbf{R}}^{-1}(\underline{\mathbf{y}} - \underline{\mathbf{H}}\underline{\mathbf{x}}^a)]$$

As with Optimal Interpolation, and the Kalman Filter, the challenge in data assimilation is how to estimate  $\underline{\mathbf{B}}$  and  $\underline{\mathbf{R}}$ , as well as proper construction of  $\underline{\mathbf{H}}$ .

$\underline{\mathbf{R}}$  usually a diagonal matrix, as all observation errors are assumed to be uncorrelated. An exception is nadir-sounding satellites, with vertical observation error correlations

# Variational Schemes

Minimize a cost-function:

$$J(\underline{\mathbf{x}}^a) = (1/2)[(\underline{\mathbf{x}}^a - \underline{\mathbf{x}}^f) \underline{\mathbf{B}}^{-1}(\underline{\mathbf{x}}^a - \underline{\mathbf{x}}^f)] + (1/2)[(\underline{\mathbf{y}} - \underline{\mathbf{H}}\underline{\mathbf{x}}^a) \underline{\mathbf{R}}^{-1}(\underline{\mathbf{y}} - \underline{\mathbf{H}}\underline{\mathbf{x}}^a)]$$

As with Optimal Interpolation, and the Kalman Filter, the challenge in data assimilation is how to estimate  $\underline{\mathbf{B}}$  and  $\underline{\mathbf{R}}$

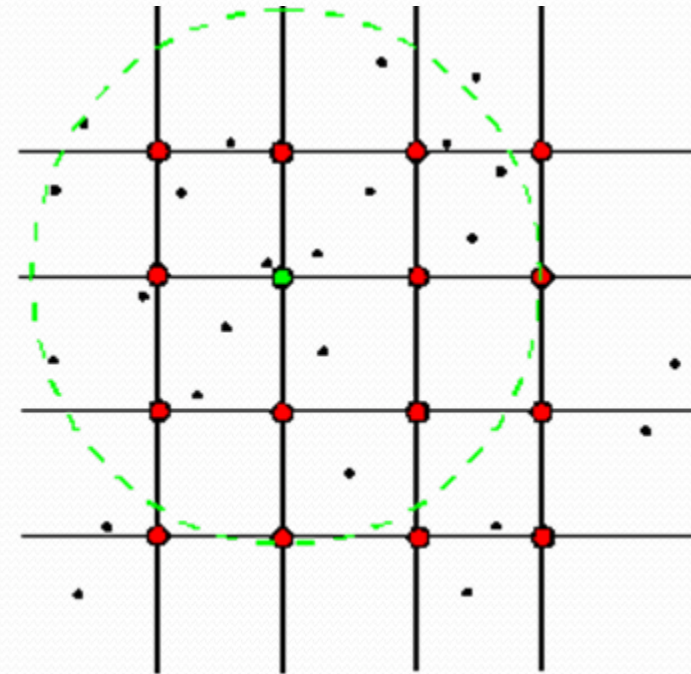
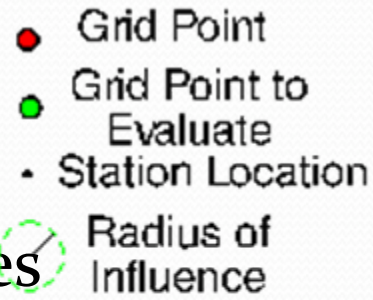
$\underline{\mathbf{B}}$  can take many forms. It can be created by:

- Declaring a Gaussian shape (OI)
- Using a recent climatology (3D-Var)
- Using differences in forecasts valid at analysis time (EnKF)



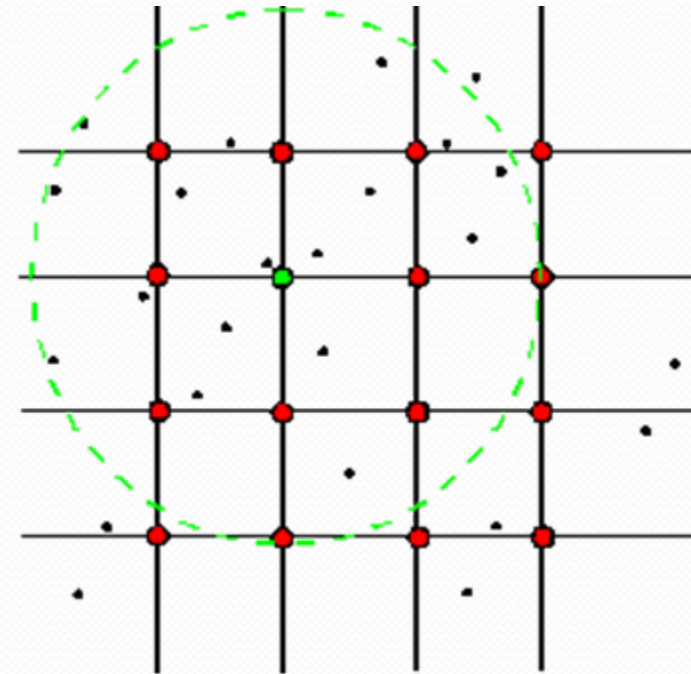
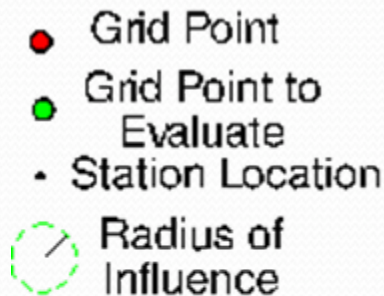
# Barnes Analysis

- The Barnes Scheme applies a Gaussian weighting function, in which the weight an observation contributes to the overall value of the grid point falls off rapidly with increasing distance from the point.



# Barnes Analysis

- Since the tails of a Gaussian function are infinite, in practice a **radius of influence** is chosen such that stations outside the circle about the gridpoint are not considered.



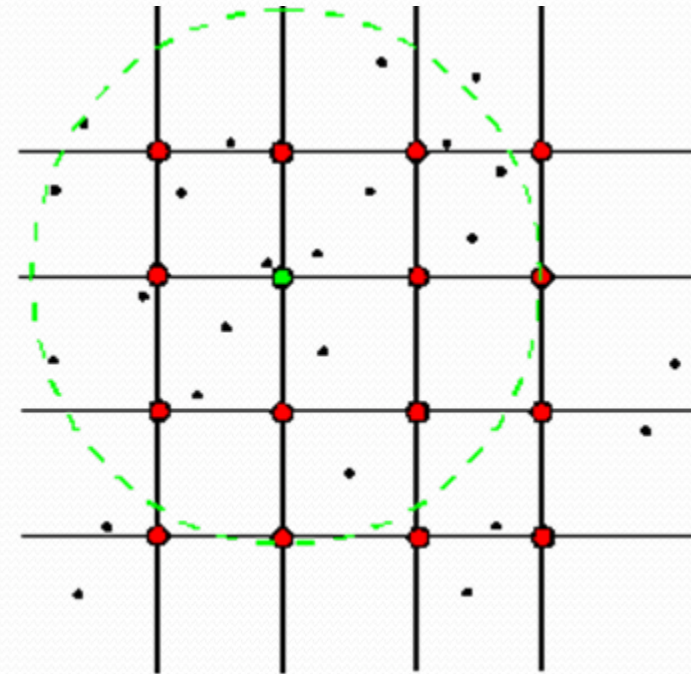
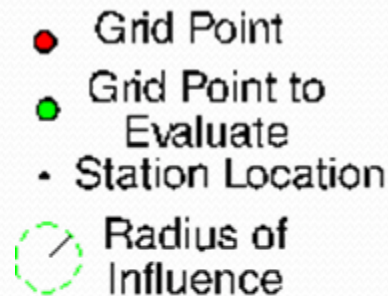


# Barnes Analysis

- For each gridpoint, stations within the radius of influence are assigned a **weight value** “W” using the formula:

$$W_i = e^{-(d/R)^2}$$

where d is the distance from the observation to the gridpoint and R is the radius of influence.

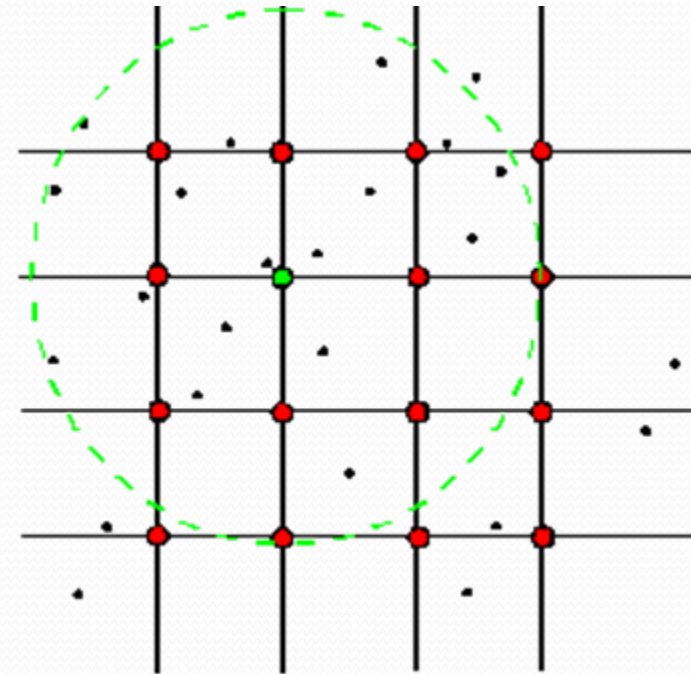
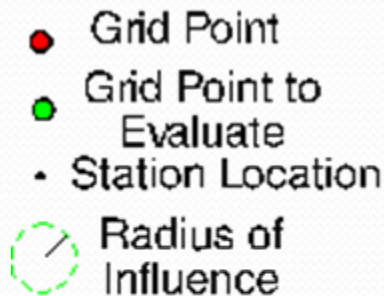


# Barnes Analysis

- After the weights are determined the analysis value at the gridpoint is determined by:

$$X_g = \frac{\sum W_i X_i}{\sum W_i}$$

This is known as the first pass of the scheme

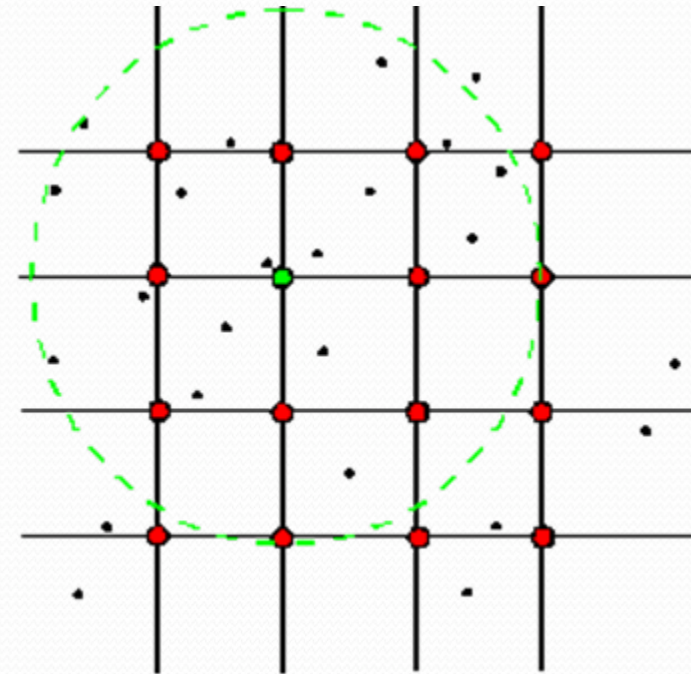
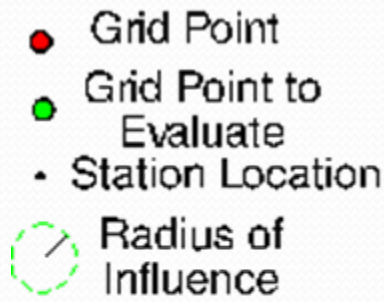




# Barnes Analysis

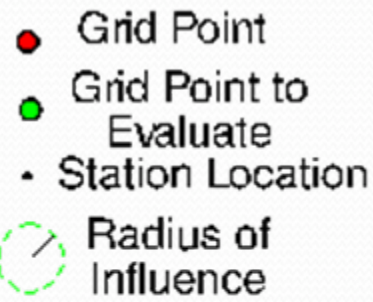
- If more than 1 iteration of the scheme is desired (typically 2 **passes** are preformed), a method known as successive correction is applied.
- Each correction step can be represented as:

$$X'_g = X_g + \frac{\sum W'_i (X_i - X_g)}{\sum W'_i}$$



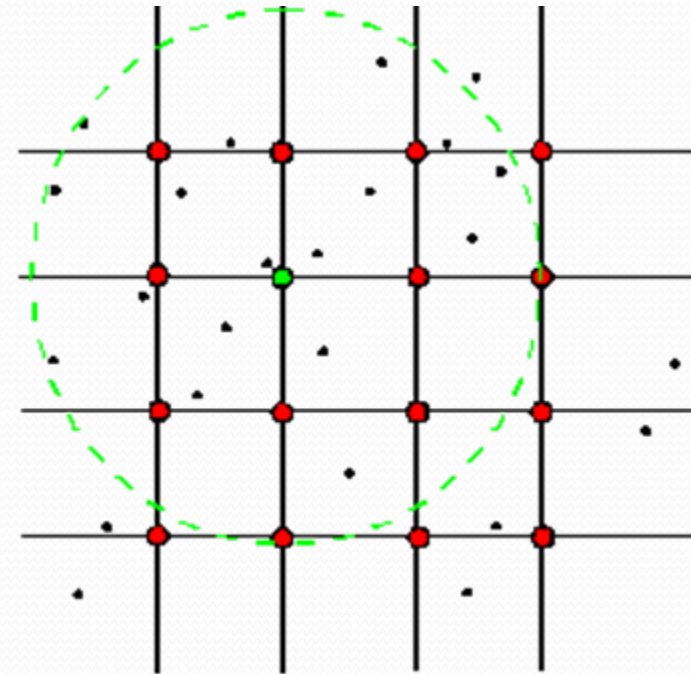
# Barnes Analysis

- A new parameter called the **convergence parameter** (GAMMA) is used to control the amount of smoothing.



$$W_i = e^{-(d/R)^2} \quad W'_i = e^{-(d/RR')^2}$$

where  $d$  is the distance from the observation to the gridpoint and  $R$  is the radius of influence

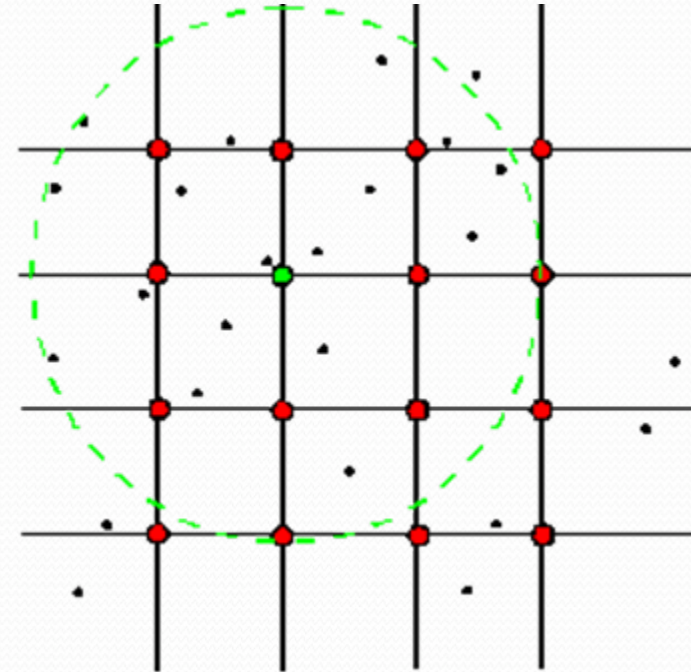




# Barnes Analysis

- The convergence parameter gamma ranges between 0 and 1.
  - A value between .2 and .3 is generally assumed.
- Grid Point  
● Grid Point to Evaluate  
• Station Location  
○ Radius of Influence

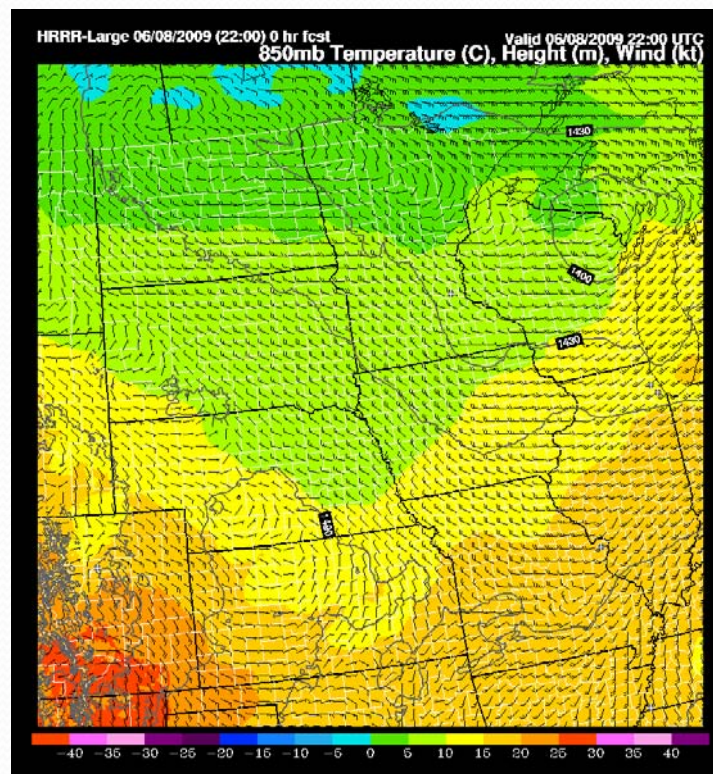
$$W_i = e^{-(d/R)^2} \quad W'_i = e^{-(d/R\Gamma)^2}$$





# Barnes Analysis in IDV

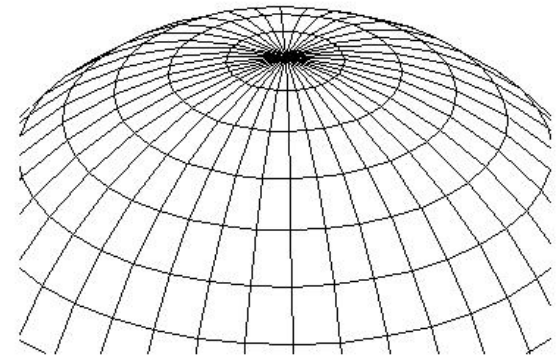
- The resulting grid can be displayed using any of the Gridded Data Displays.
- There are 5 parameters for you to set:
  - Spacing
  - Grid Size
  - Passes
  - Search Radius
  - Gain<sup>?</sup>





# Barnes Analysis in IDV

- **Spacing.** You can set the grid spacing as follows:
  - Automatic - grid spacing will be calculated from the observation density
  - Degrees - use a specific lat/lon spacing
  - Points - set the number of grid points in the x and y direction
- **Grid Size.** Specify the grid spacing if not using automatic calculation. [?]





# Barnes Analysis in IDV

- **Passes.** Set the number of passes for the Barnes analysis to do
  - 4 passes recommended for analyzing fields where derivative estimates are important (Ref: Barnes 1994b)
  - 3 passes recommended for all other fields (with gain set to 1.0) (Ref: Barnes 1994c "Two pass Barnes Objective Analysis schemes now in use probably should be replaced by appropriately tuned 3pass or 4pass schemes")
  - 2 passes only recommended for "quick look" type analyses.
  - 1 pass is rather rough
  - 5 is right out (Book of Armaments)





# Barnes Analysis in IDV

- **Search Radius.** Set the search radius (in grid units) for the weighting of points in determining the value at a specific grid point. Should be in the range 0.2 to 1.0.
  - Data are fitted more closely with a gain of 0.2 (at the expense of less overall accuracy over the entire grid); larger values smooth more.
- **Gain.** Set the factor by which scale Length is reduced for the second pass. Should be in the range 0.2 to 1.0.
  - Data are fitted more closely with a gain of 0.2 (at the expense of less overall accuracy over the entire grid); larger values smooth more.
  - Suggested default: 1.0 Set the gain for each pass after the first.





# Now it is your turn

- Launch IDV!
- Load in sonde data
- Load in surface data
- Make some analyses





# Load in the sonde and METAR data

- Data

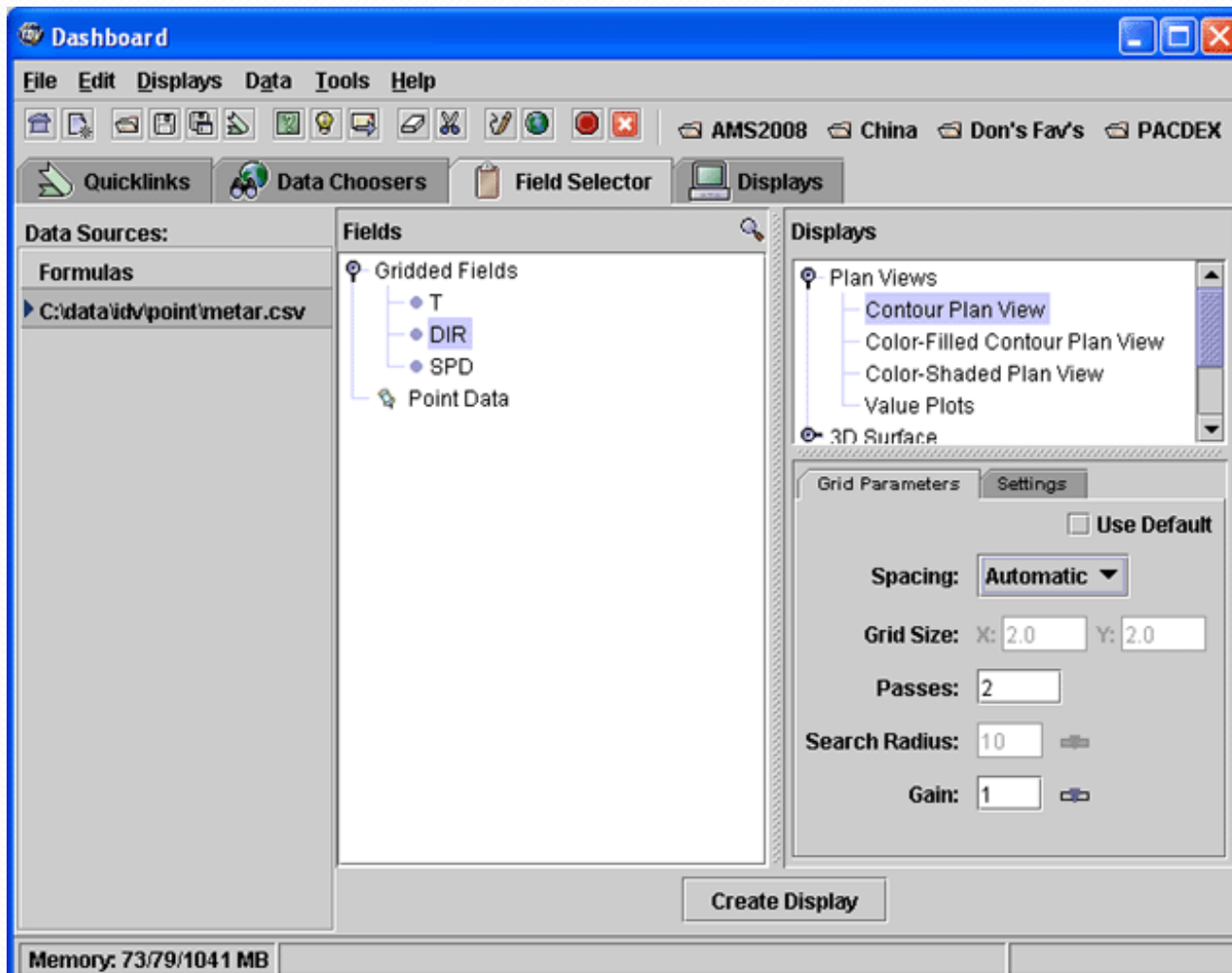
- Choose Data
  - Upper Air Observations
    - Connect
      - Most Recent
        - “Add Source”

- Data

- Choose Data
  - Surface Observations
    - Connect
      - Most Recent
        - “Add Source”



# Barnes Analysis in IDV



Default Settings:

- Spacing
  - 2 degrees
- Passes
  - 2
- Search Radius
  - 10
- Gain
  - 1
- Field
  - Pressure
- Level
  - Surface



# Explore these areas

- See what happens if you change the grid-spacing from the default 2-degrees to 0.5-degrees or 10-degrees
- See what happens if you change the number of passes from 2 to 1 or 10
- See what happens if you change the search radius from 10 to 1
- See what happens if you change the gain from 1 to 0.1
- See what happens if you look at different fields ( $T$ ,  $T_d$ )
- See what happens if you look at surface (METAR) data as opposed to 500mb data
- **Upload your favorite analyses to share with us**

# Barnes Analysis in IDV

- References Barnes, S.L., 1994a: Applications of the Barnes objective analysis scheme Part I: Effects of undersampling, wave position, and station randomness. J. Atmos. Oceanic Technol. 11, 1433-1448.
- Barnes, S.L., 1994b: Applications of the Barnes objective analysis scheme Part II: Improving derivative estimates. J. Atmos. Oceanic Technol. 11, 1449-1458.
- Barnes, S.L., 1994c: Applications of the Barnes objective analysis scheme Part III: Tuning for minimum error. J. Atmos. Oceanic Technol. 11, 1459-1479.
- <http://www.asp.ucar.edu/colloquium/1992/notes/part1/node120.html>