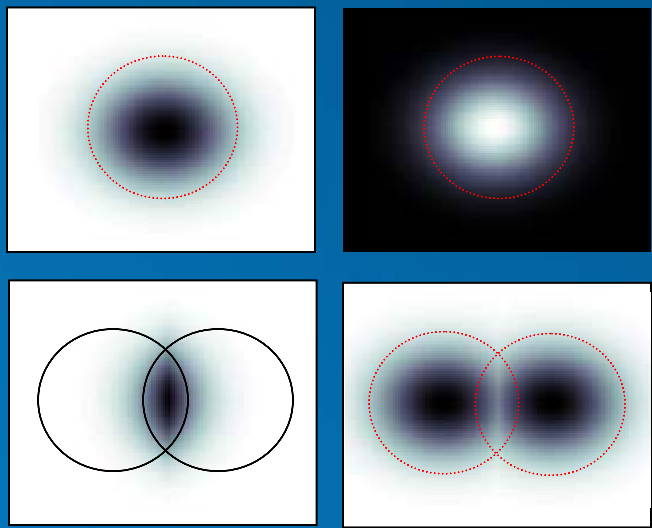
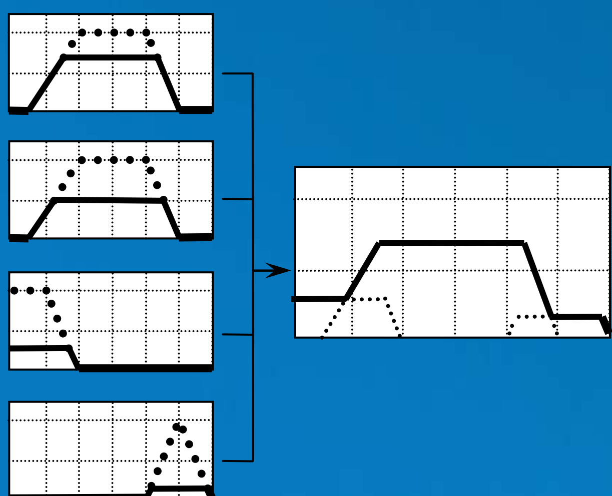
Fuzzy Logic
Philosophy, Theory and Applications

John K. Williams
NCAR Research Applications Laboratory
jkwillia@ucar.edu





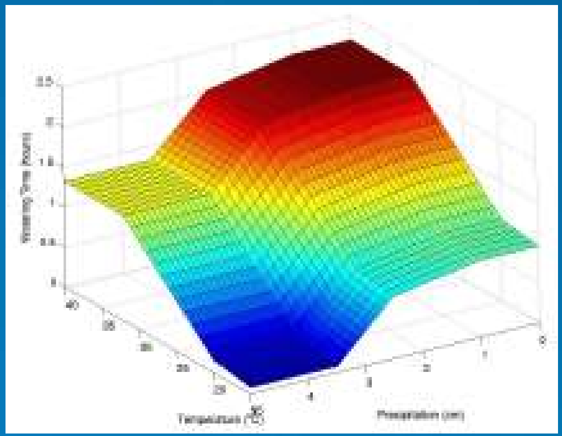


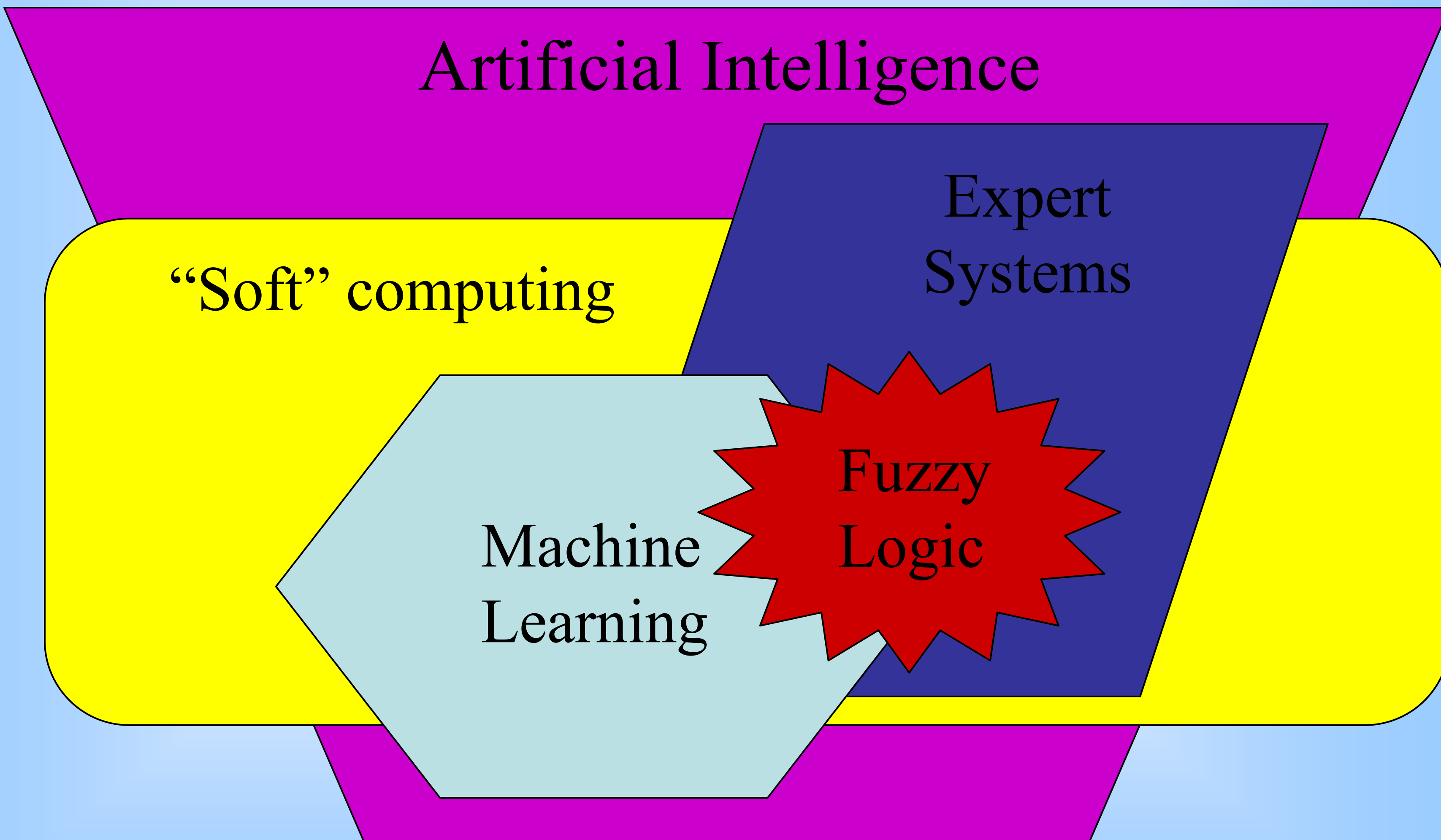
Photo: Paul Bowen

Artificial Intelligence Workshop, Texas A&M University at Corpus Christi, 12-13 January 2007

What is Fuzzy Logic?

- *(narrow)* A logical system involving *fuzzy sets*: classes of objects with unsharp boundaries in which membership is a matter of degree.
- *(common usage)* The theory and practice of computing using fuzzy sets.
- *(broad)* Any solution that mimics the reasoning of a human expert, preserving information through the use of continuous “membership” or “interest” values until production of an output.

Taxonomy of Fuzzy Logic



Why Use Fuzzy Logic? (1)

"The guiding principle of soft computing is: Exploit the tolerance for imprecision, uncertainty, and partial truth to achieve tractability, robustness, and low solution cost…. What makes [fuzzy logic] so powerful is the fact that most of human reasoning and concept formation is linked to the use of fuzzy rules. By providing a systematic framework for computing with fuzzy rules, [fuzzy logic] greatly amplifies the power of human reasoning."

– Lotfi Zadeh

Why Use Fuzzy Logic? (2)

"So far as the laws of mathematics refer to reality, they are not certain. And so far as they are certain, they do not refer to reality."
– Albert Einstein

"As complexity rises, precise statements lose meaning and meaningful statements lose precision." – Lotfi Zadeh

Imprecision is a fact of life!

Why Use Fuzzy Logic? (3)

- FL systems use information efficiently
  - All available evidence used, propagated until final "defuzzification"
  - Robust to uncertain, missing or corrupted data
- FL encodes human expert knowledge/heuristics
  - Common-sense, easily interpreted
  - Constraints are naturally enforced
- FL systems are cheap
  - Training data are not required (but if available, they can be used to tune system)
  - Models or joint/conditional probability distributions are not needed
  - Relatively straightforward to design and implement

A Brief History of Fuzzy Logic (1)

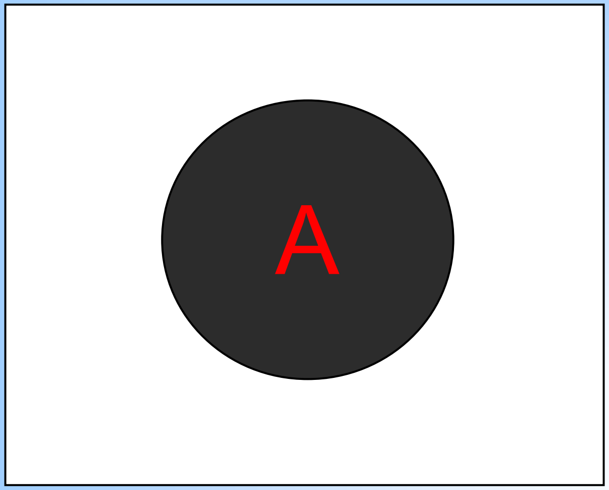
- 1937 – Max Black writes “Vagueness: An exercise in Logical Analysis” in *Philosophy of Science*
- 1965 – Lotfi Zadeh publishes “Fuzzy Sets” in *Information and Control*
- 1973 – Ebrahim Mamdani and Sedrak Assilian build fuzzy logic controller for steam engine
- 1978 – Laritz Peter Holmblad and Jens-Jorgen Østergaard develop and commercialize fuzzy logic controller for industrial cement kilns
- 1979 – Hans Berliner’s BKG 9.8 program beats world backgammon champion Luigi Villa, 7-1

A Brief History of Fuzzy Logic (2)

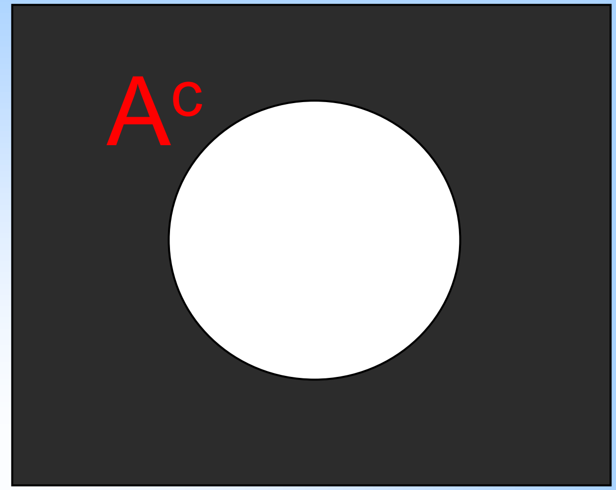
- 1987 – Subway system using predictive fuzzy controllers enters service in Sendai, Japan
- *Explosion of applications: medical expert systems, consumer electronics and appliances, financial analysis, industrial process control, ….*

- 1993 – MIT Lincoln Laboratories develops Machine Intelligent Gust Front Algorithm (MIGFA)
- 1994 – NCAR/RAP develops Doppler radar Microburst Automatic Detection (MAD) algorithm
- 1998 – NCAR/RAP develops NCAR Improved Moments Algorithm (NIMA) for wind profilers

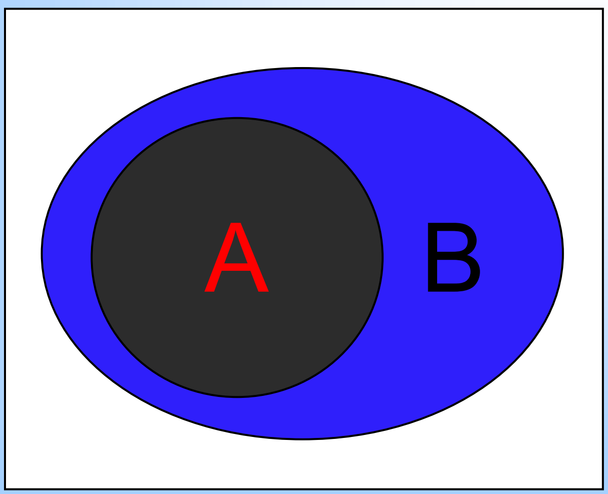
Classical Sets (1)



Set A



Complement (Not A)

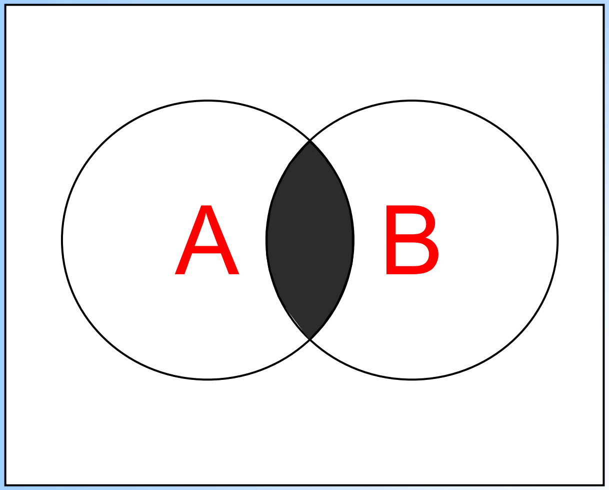


Inclusion: $A \subset B$

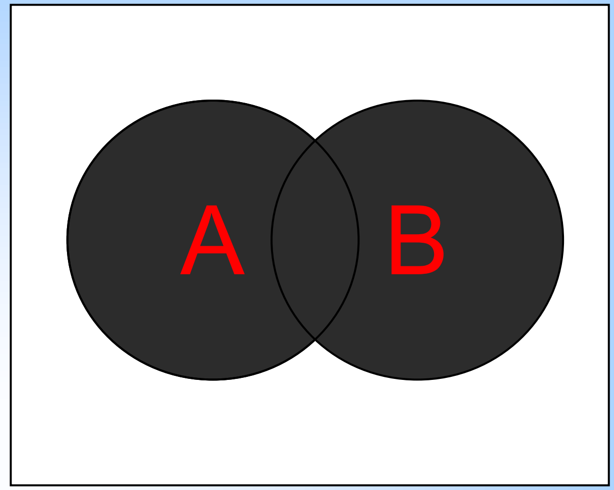
"A is a subset of B"

(i.e., membership in A implies membership in B)

Classical Sets (2)

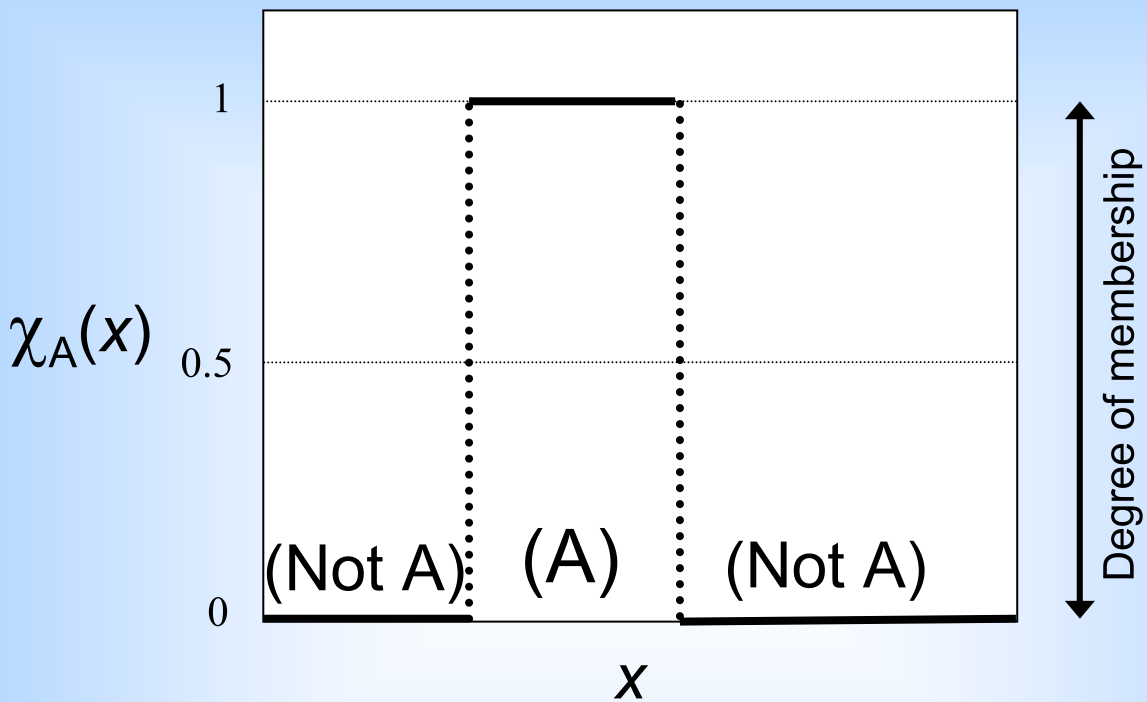


Intersection (AND): $A \cap B$



Union (OR): $A \cup B$

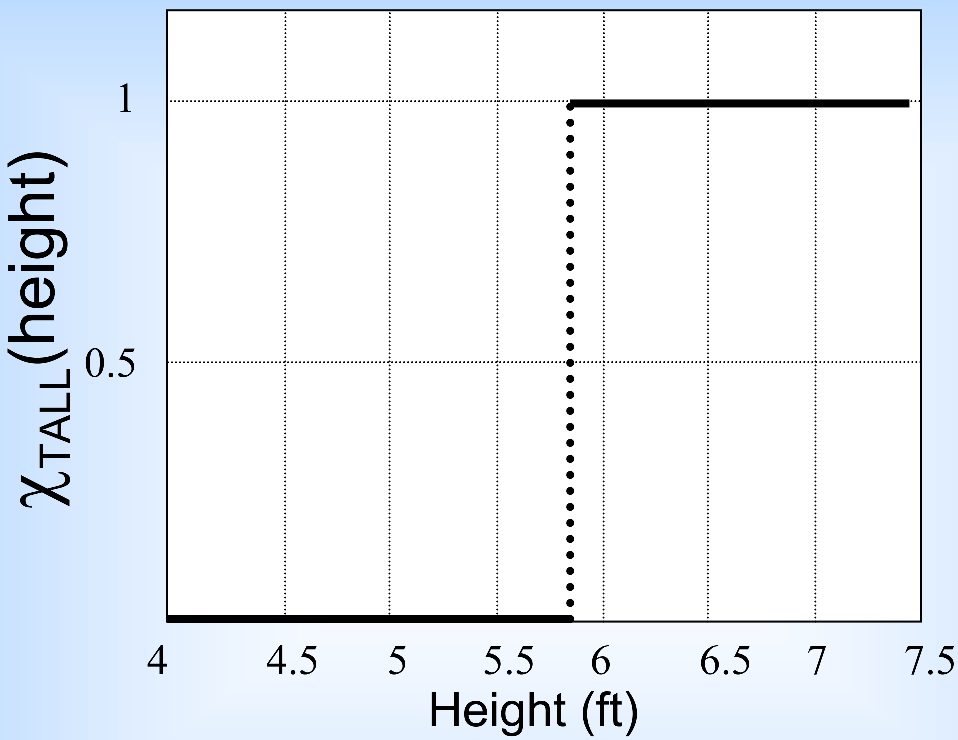
Classical Sets (3)



The *characteristic function* of a set A is 1 for elements in A, and 0 otherwise:

$\chi_A(x) = 1$ if $x \in A$ and $\chi_A(x) = 0$ if $x \notin A$

Classical Sets (4)



Example: “This person is tall.”

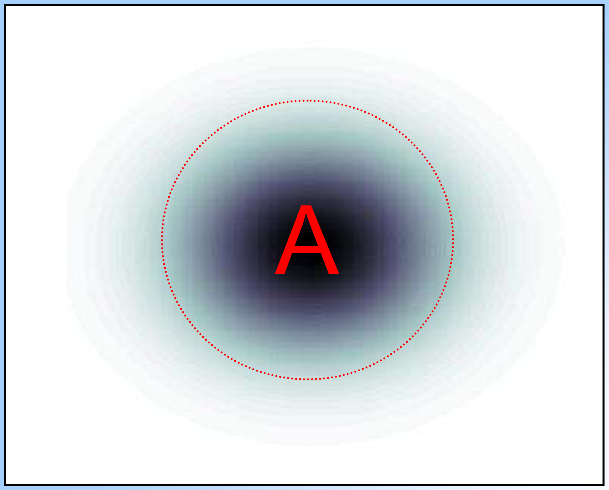
(tall people are those with heights > 5’ 10’’)

Fuzzy Sets (1)

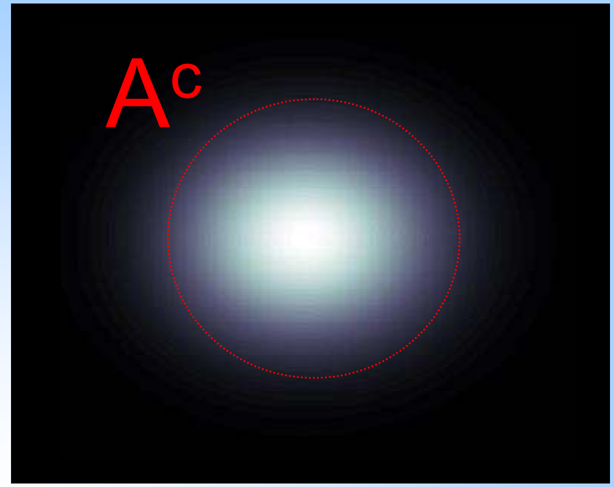
“Words [resemble] those nebulous masses familiar to the astronomer, in which a clear and unmistakable nucleus shades off on all sides, through zones of decreasing brightness, to a dim marginal film that seems to end nowhere, but to lose itself imperceptibly in the surrounding darkness.” – James A. H. Murray

“Think of arm chairs and reading chairs and dining-room chairs, and kitchen chairs, chairs that pass into benches, chairs that cross the boundary and become settees, dentist’s chairs, thrones, opera stalls, seats of all sorts…and you will perceive what a lax bundle in fact is this simple straightforward term.” – H. G. Wells

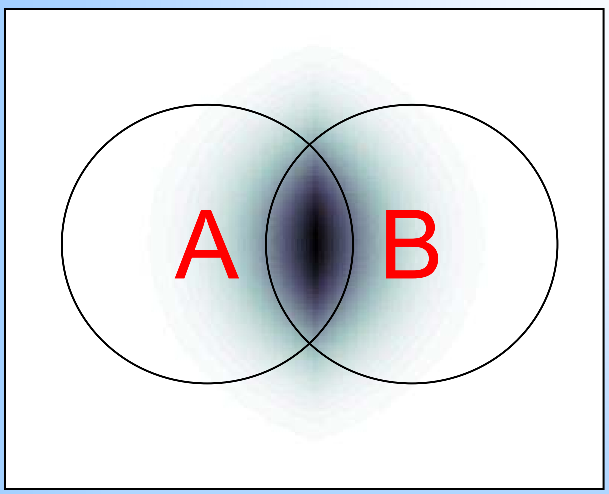
Fuzzy Sets (2)



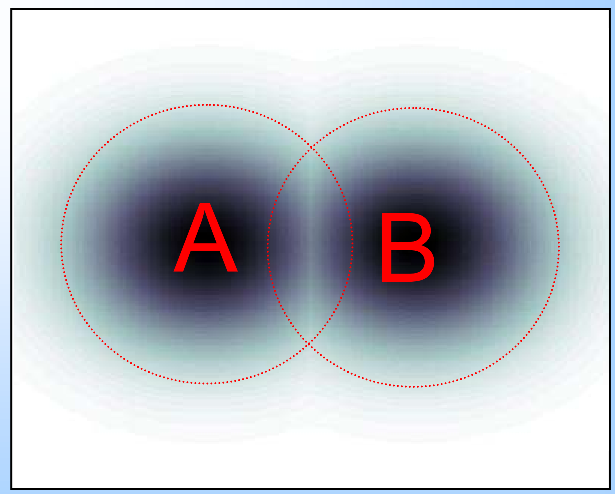
Set A



Complement (Not A)

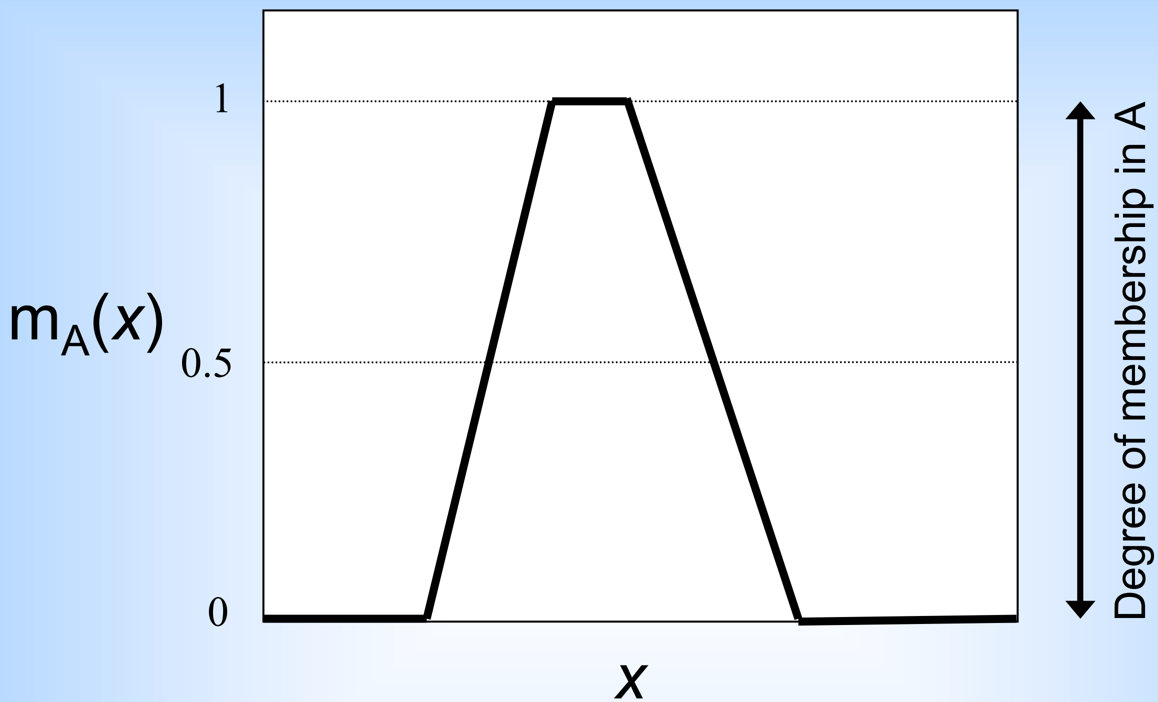


Intersection (AND): $A \cap B$



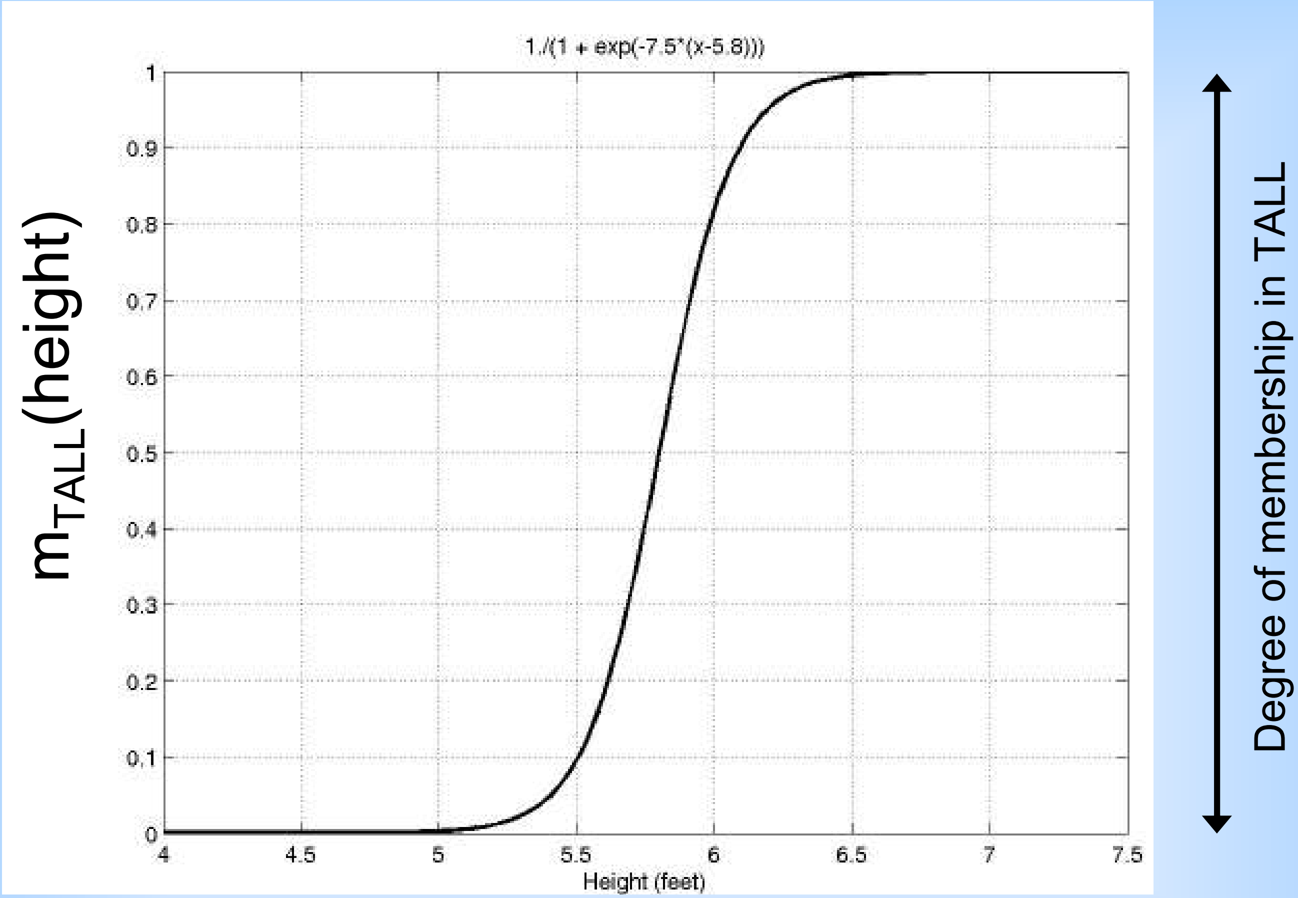
Union (OR): $A \cup B$

Fuzzy Sets (3)



The *membership function* of a fuzzy set A comprises a value for each element representing its degree of membership in set A: $m_A(x) \in [0, 1]$ for all x

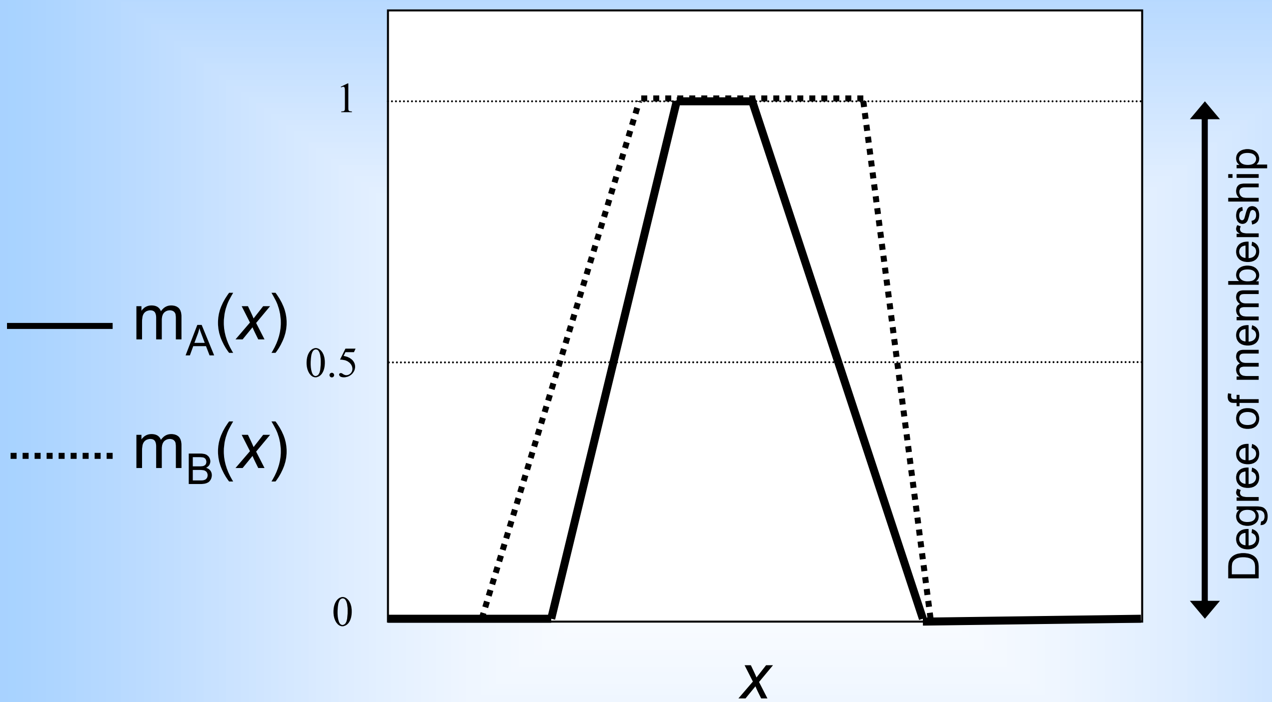
Fuzzy Sets (4)



Example: “This person is tall.”

(“tallness” has degrees!)

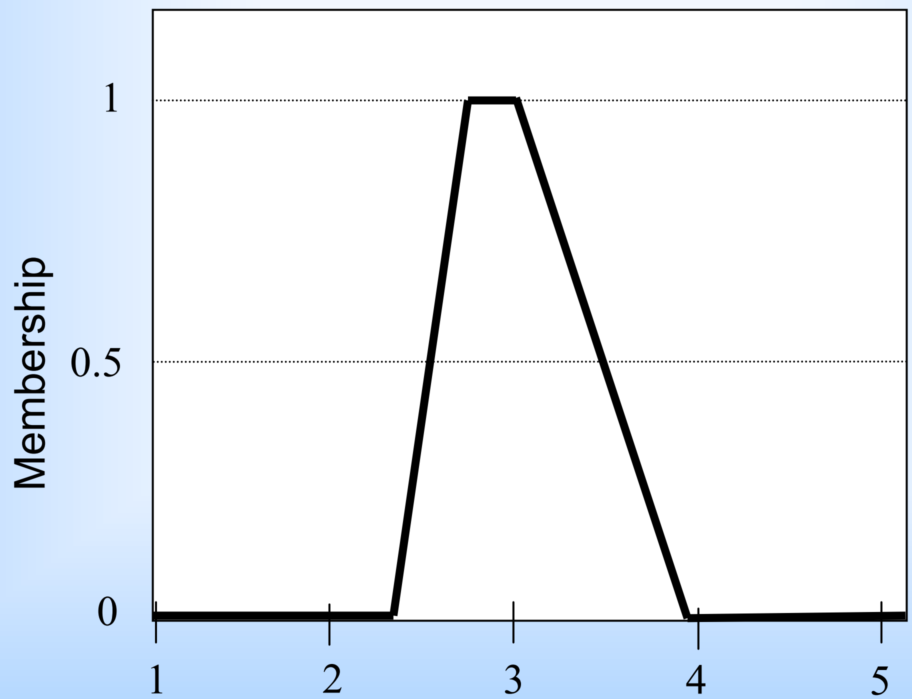
Fuzzy Subsets



$A \subset B$ ("A is a subset of B") if $m_A(x) \leq m_B(x)$ for all elements x, i.e., if membership in A implies membership in B to at least an equal extent

Fuzzy Numbers

A fuzzy set having a continuous membership function such that $\{x\colon m_A(x) = 1\}$ is either a single element or a connected region (e.g., an interval).



Fuzzy “3”

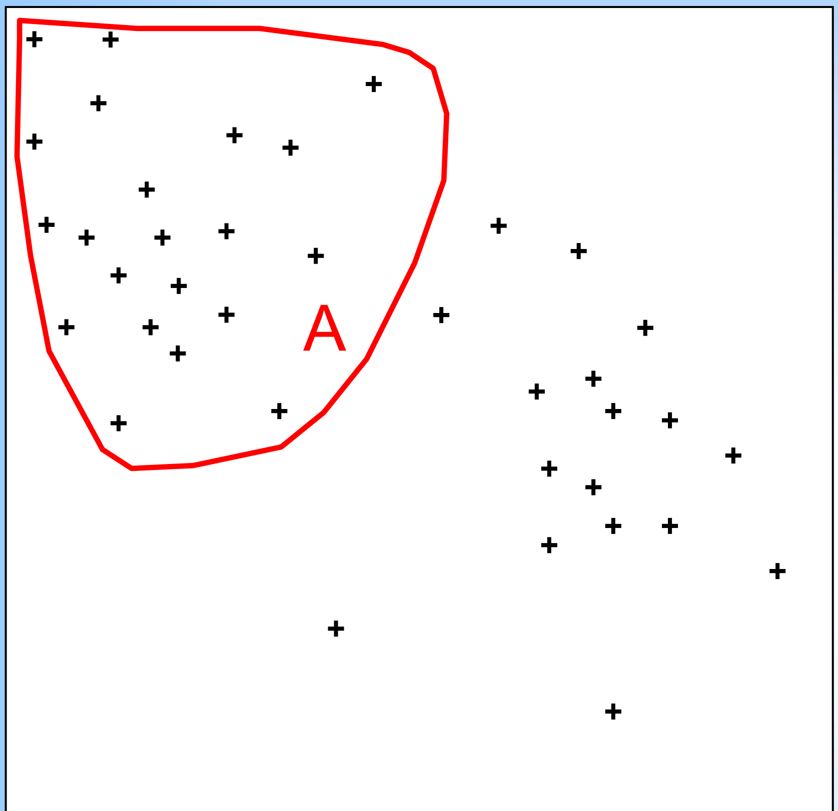
Computing with Fuzzy Numbers

- The *extension principle* turns ordinary functions to maps between fuzzy sets: if *f*: X $\rightarrow$ Y, and A is a fuzzy set in X, then

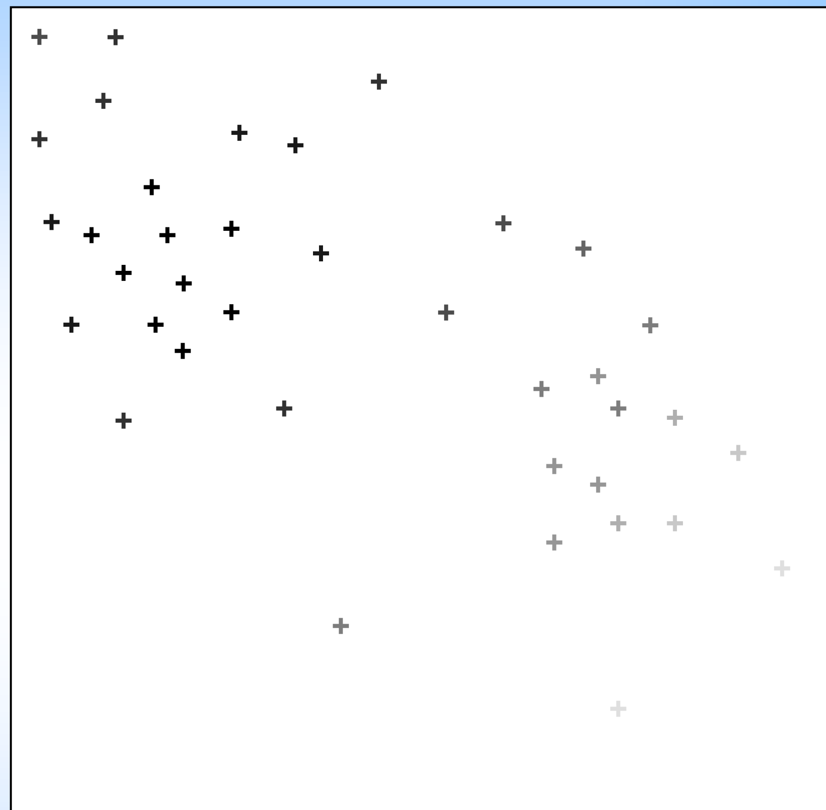
$$m_{f(A)}(y) = \sup\left\{m_A(x) \mid f(x) = y\right\}$$

- One application is the propagation of measurement uncertainty through a calculation.

Fuzzy Clustering



Classical or “crisp” cluster A



Fuzzy cluster A

Produces cluster membership functions—each data point has membership in each fuzzy cluster

Fuzzy *c*-Means (FCM) Clustering

- Step 1: Choose $m > 1$ (small for "tight" clusters)
- Step 2: Initialize cluster prototypes $\{\mathbf{v}_i \mid 1 \le i \le c\}$
- Step 3: Compute memberships for data vectors $\mathbf{x}_k$

$$m_{C_i}(\mathbf{x}_k) = \left(\sum_{j=1}^{c} \left(\frac{d(\mathbf{x}_k, \mathbf{v}_i)}{d(\mathbf{x}_k, \mathbf{v}_j)} \right)^{\frac{1}{m-1}} \right)^{-1}$$

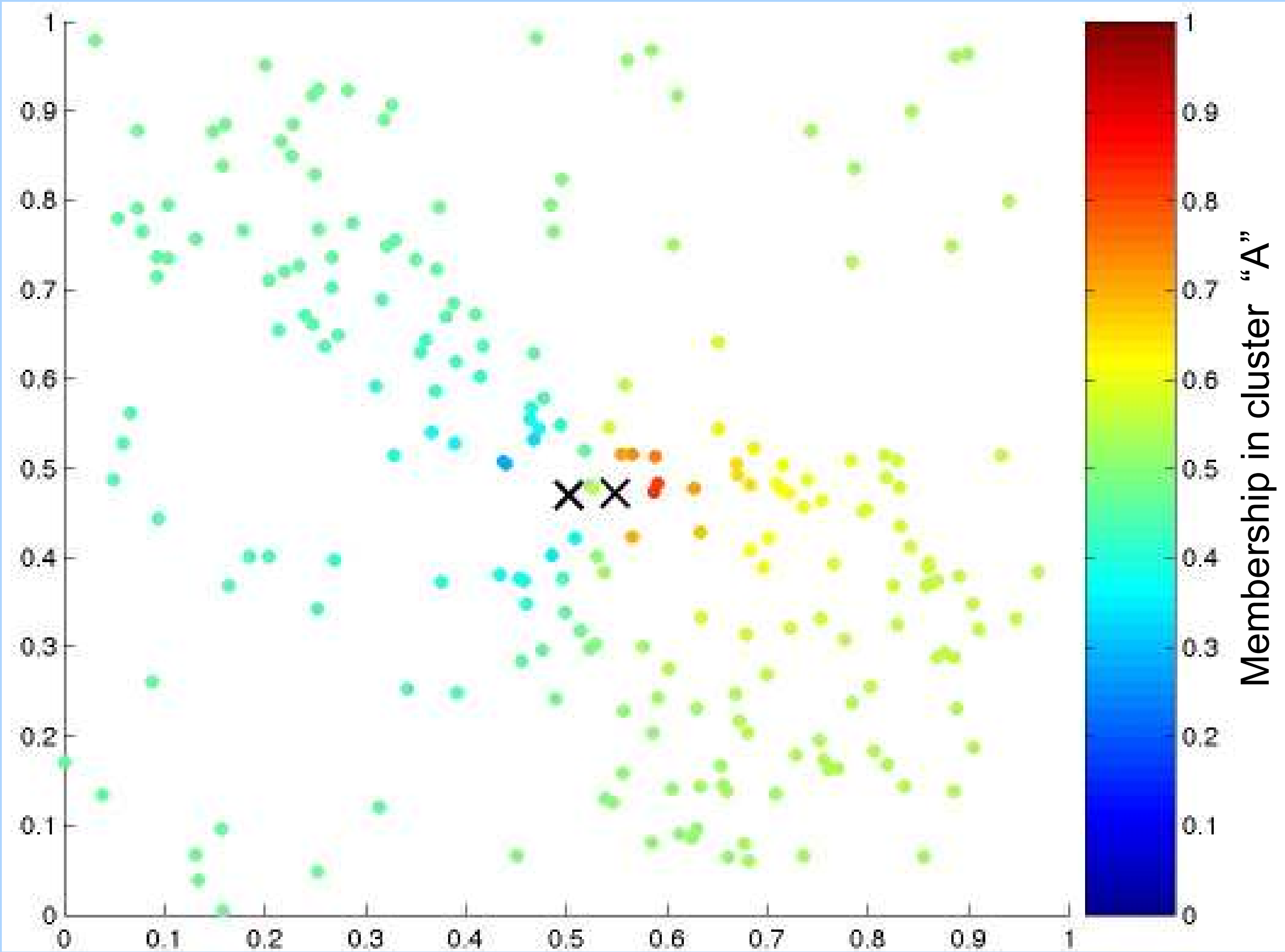
(*d* is distance)

- Step 4: Compute new cluster protypes

$$\mathbf{v}_i = \frac{\sum_{k=1}^{c} \mathbf{x}_k \left(m_{C_i}(\mathbf{x}_k) \right)^m}{\sum_{k=1}^{c} \left(m_{C_i}(\mathbf{x}_k) \right)^m}$$

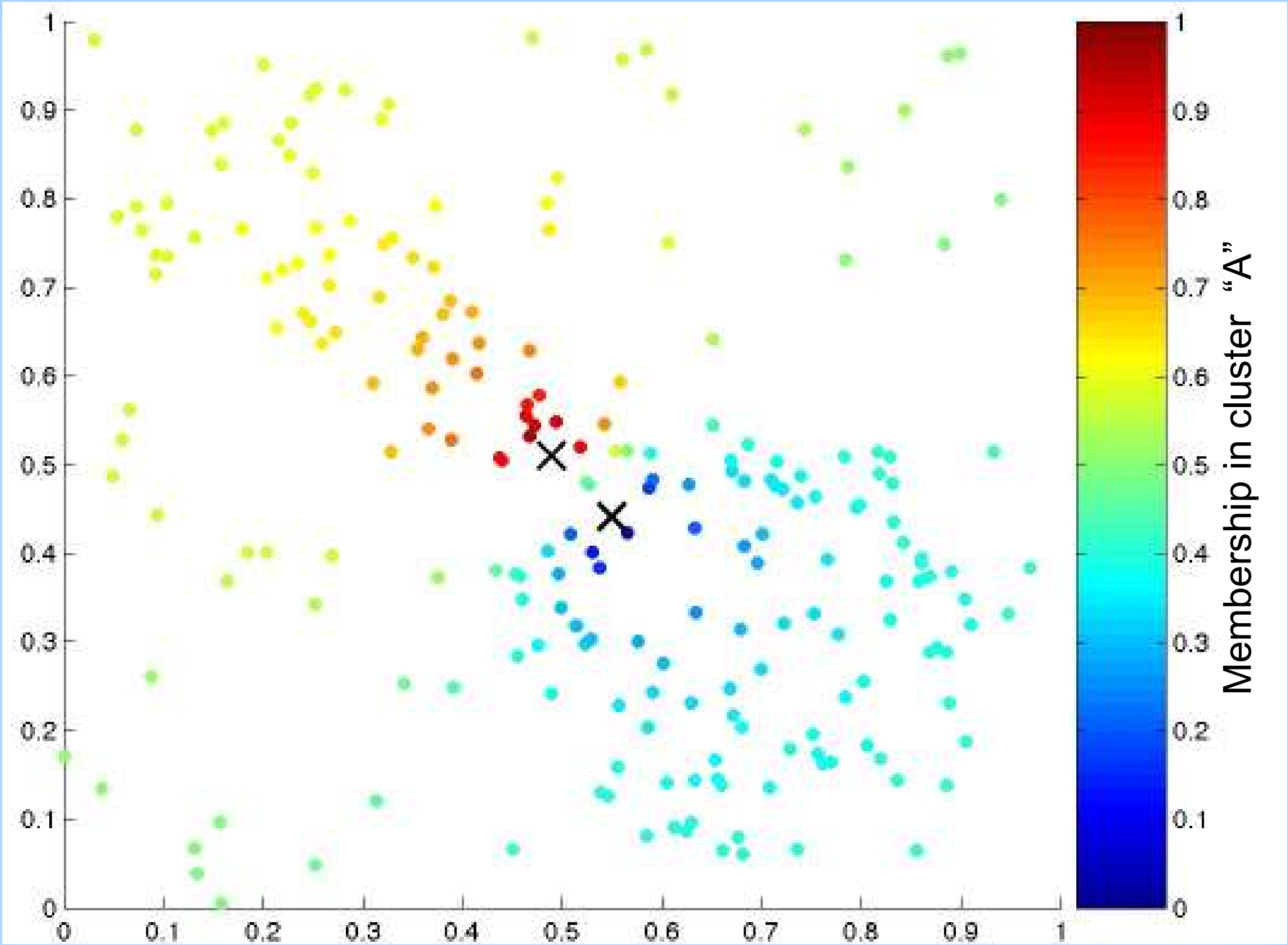
- Step 5: If change in all protypes is small, stop. Otherwise, return to step 3.

FCM Clustering Example (1)



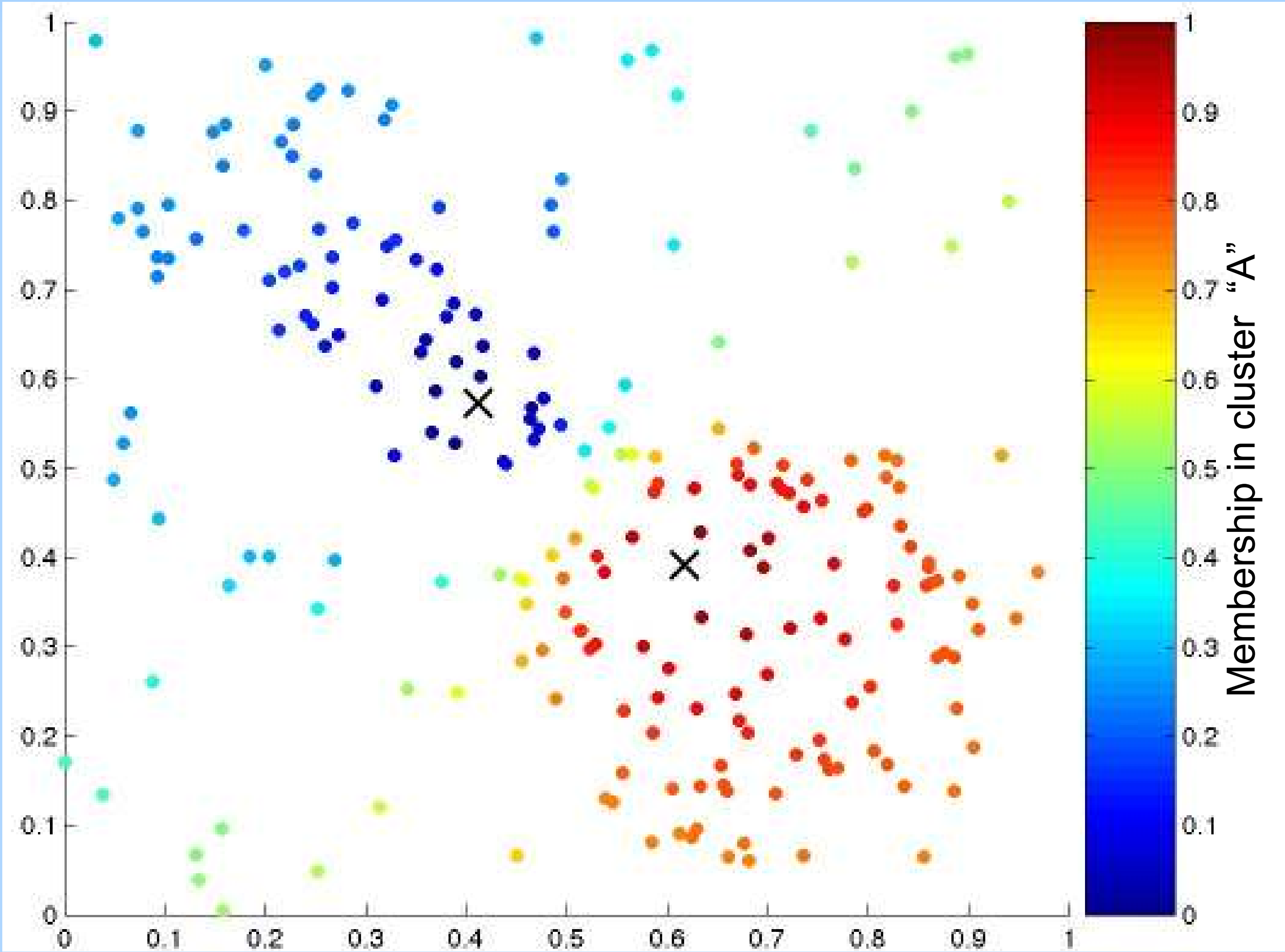
Iteration 1

FCM Clustering Example (2)



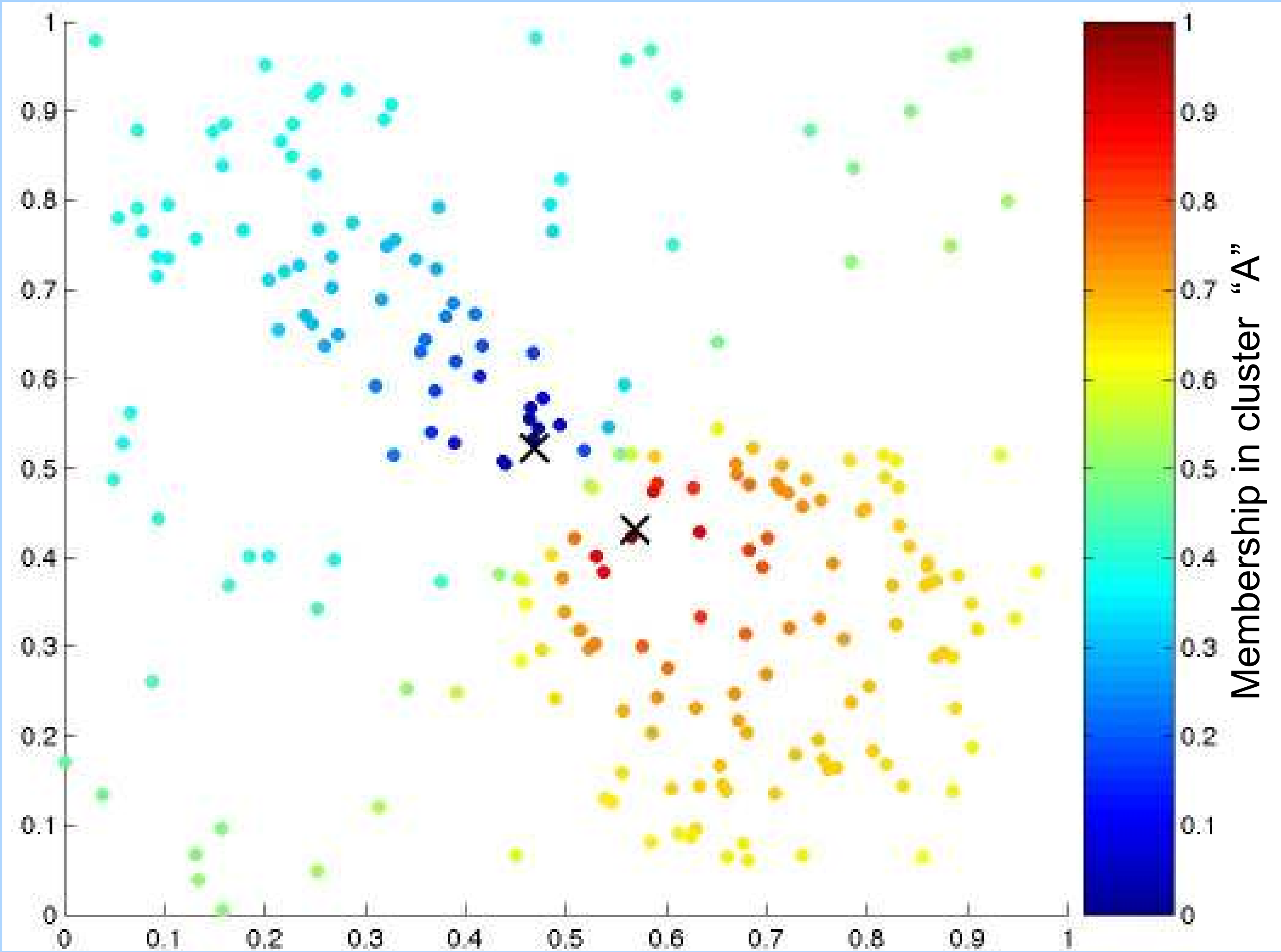
Iteration 2

FCM Clustering Example (3)



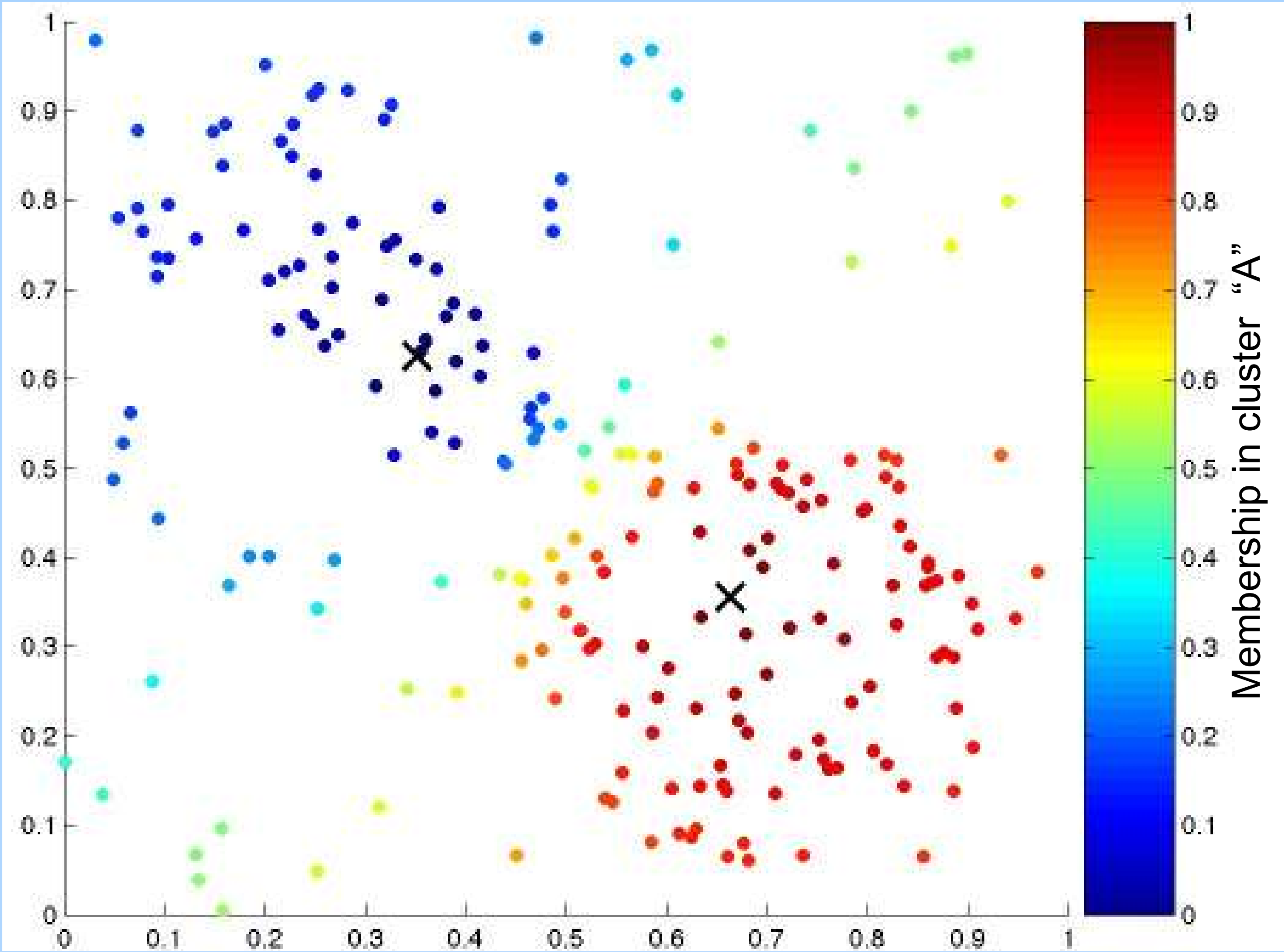
Iteration 3

FCM Clustering Example (4)



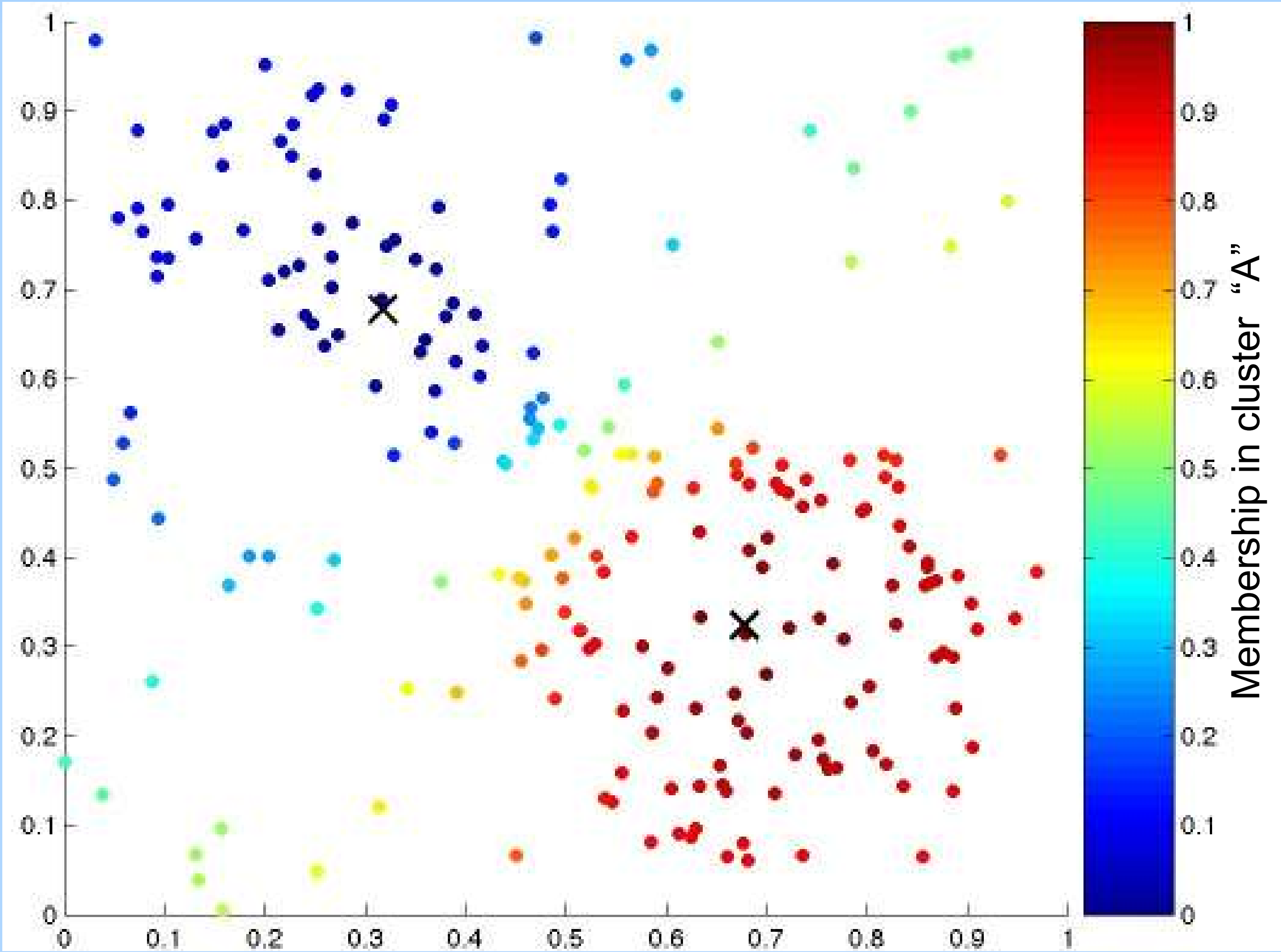
Iteration 4

FCM Clustering Example (5)



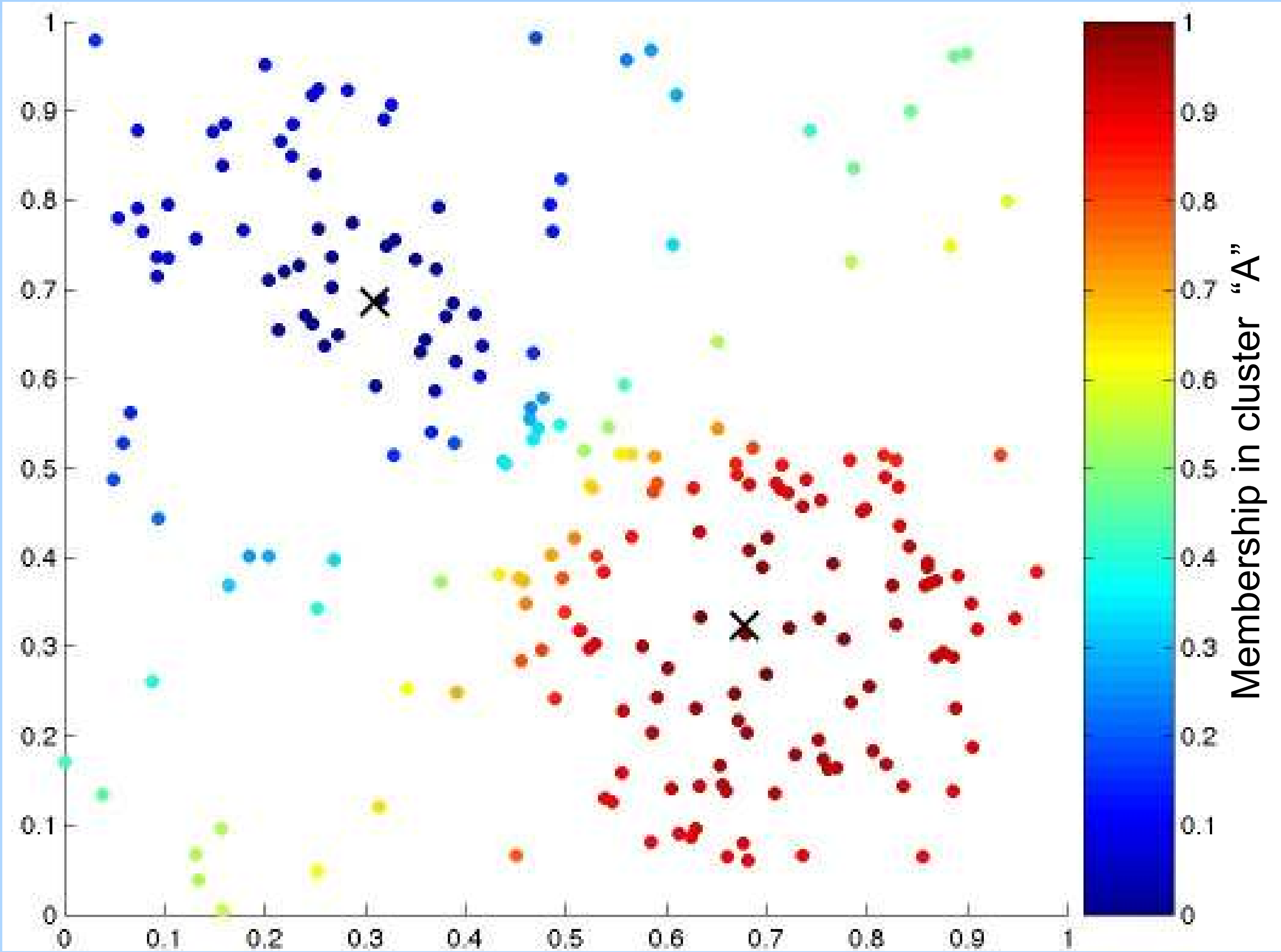
Iteration 5

FCM Clustering Example (6)



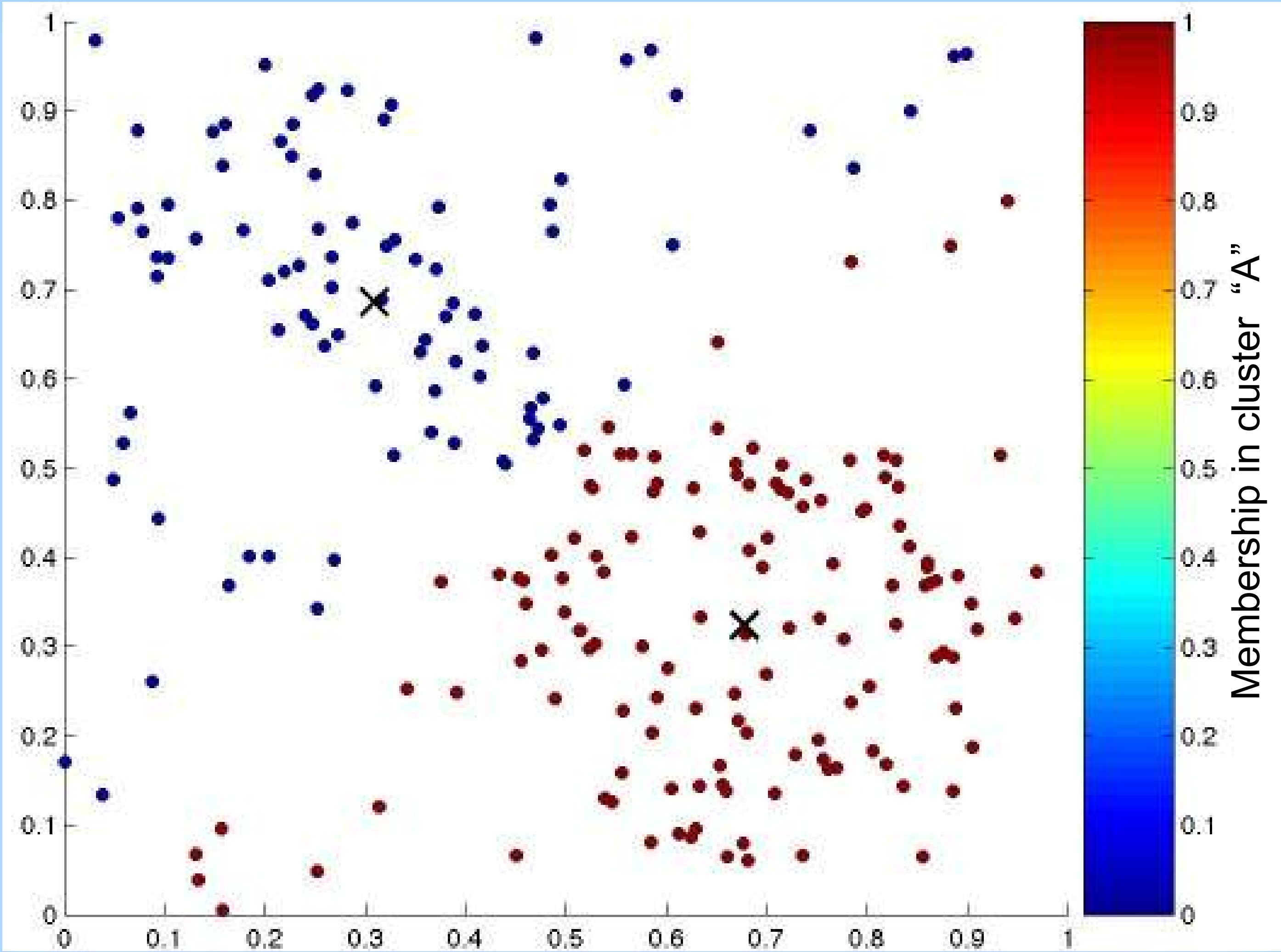
Iteration 6

FCM Clustering Example (7)



Iteration 7

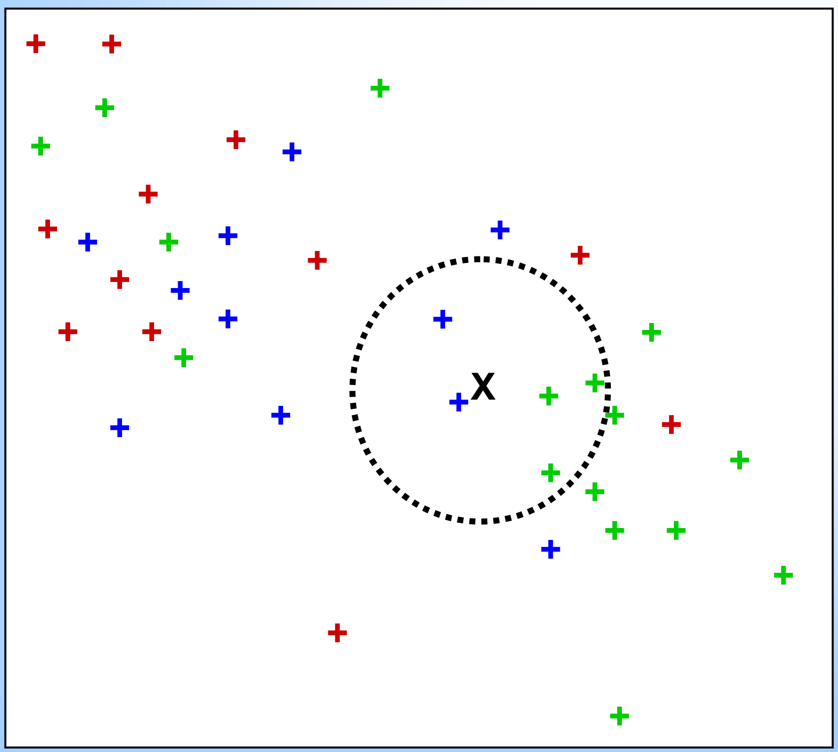
FCM Clustering Example (8)



Iteration 7 <u>defuzzified</u>

Fuzzy *k*-nearest neighbors (*k*-NN): generalizing from labeled data

Infer class membership values of a sample point ("X") based on a distance-weighted consensus of its *k* "nearest neighbors"



Here *k* = 5, and classes are "red", "blue" and "green"

Fuzzy *k*-NN (2)

- Suppose data $\{\boldsymbol{x}_j \mid 1 \le j \le N\}$ have class memberships m_{C_i} for classes C_i and we want to know the class of $\boldsymbol{x}$.
  - Choose a positive integer k, a number $m > 1$ (small values = "tight" association) and a distance metric d
  - Choose $\{\boldsymbol{y}_n \mid 1 \le n \le k\}$ to be the k nearest $\boldsymbol{x}_i$ to $\boldsymbol{x}$
  - Define the membership of $\boldsymbol{x}$ in each class C_i by

$$m_{C_i}(\mathbf{x}) = \frac{\sum_{n=1}^{k} m_{C_i}(\mathbf{y}_n)\, d(\mathbf{x},\mathbf{y}_n)^{-\frac{2}{m-1}}}{\sum_{n=1}^{k} d(\mathbf{x},\mathbf{y}_n)^{-\frac{2}{m-1}}}$$

  - Note that if $\sum_{i=1}^{N} m_{C_i}(\mathbf{y}_n) = 1$ for all $\boldsymbol{y}_n$, then $\sum_{i=1}^{N} m_{C_i}(\mathbf{x}) = 1$

Building Membership Functions (1)

Example: “This color is blue.”

m = 1 (“completely true”)

Building Membership Functions (2)

Example: “This color is blue.”

m = 0.8 (“mostly true”)

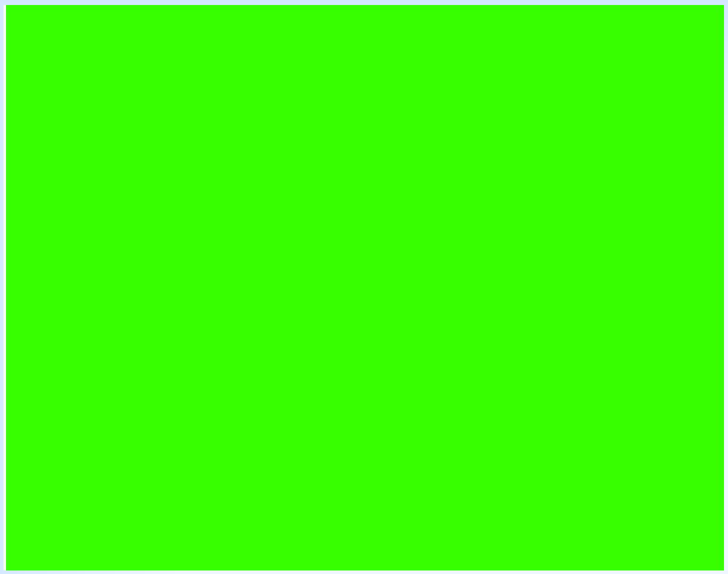
Building Membership Functions (3)

Example: “This color is blue.”

m = 0.2 (“slightly true”)

Building Membership Functions (4)

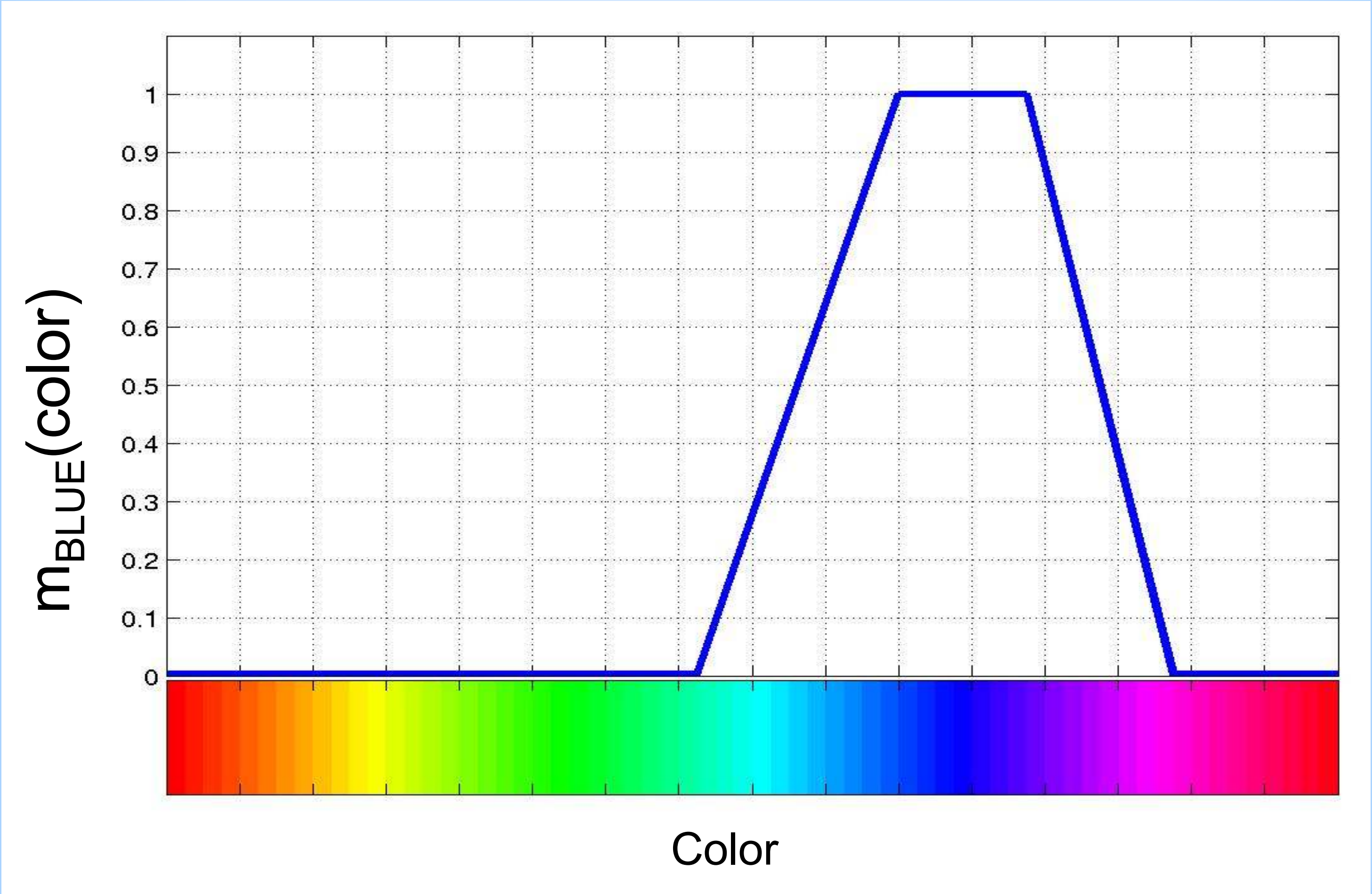
Example: “This color is blue.”



m = 0 (“not true”)

Building Membership Functions (5)

Example: “This color is blue.”



Logical Operations (1)

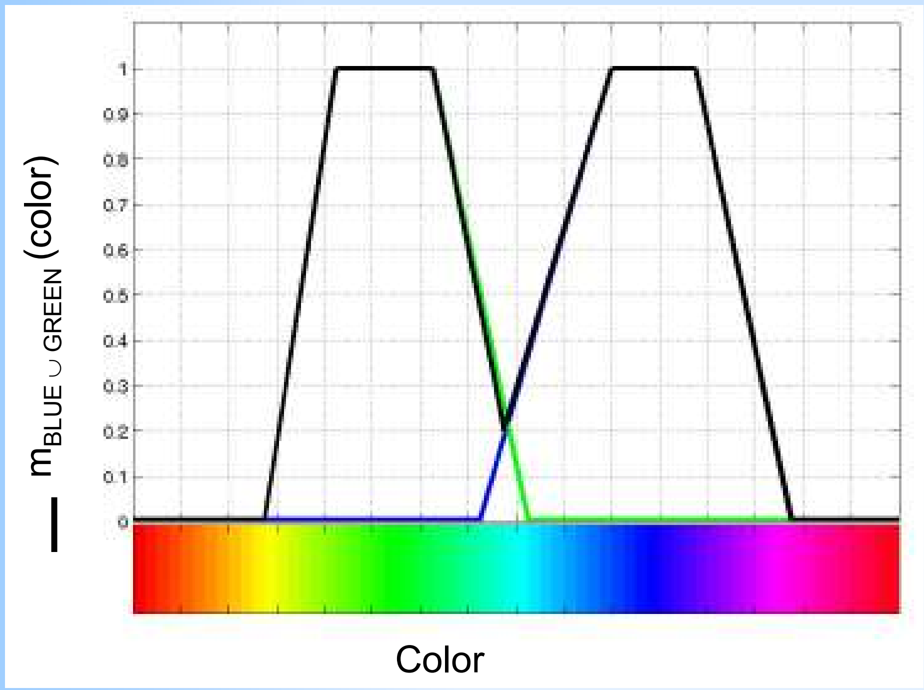
"Blue" and "NOT Blue"

m_A	m_{A^c}	
1	0	← *classical*
0.8	0.2	
0.6	0.4	
0.4	0.6	
0.2	0.8	
0	1	← *classical*

Fuzzy set complement (NOT): $m_{A^c}(x) = 1 - m_A(x)$

Logical Operations (2)

"Green", "Blue", and "Green OR Blue"

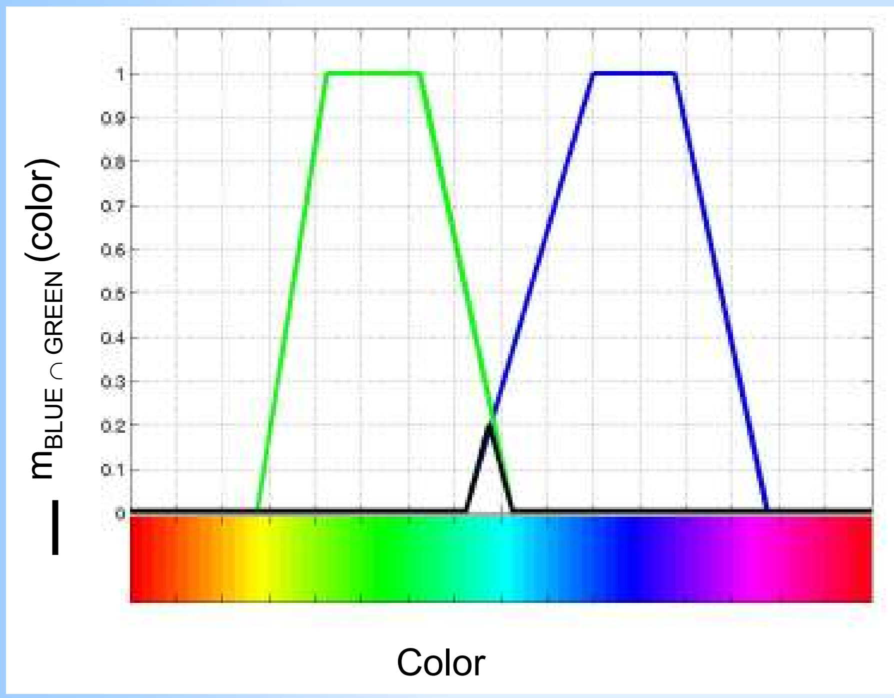


m_A	m_B	$m_{A \cup B}$	
1	1	1	← *classical*
1	0.5	1	
1	0	1	← *classical*
0.8	0.5	0.8	
0.5	0.8	0.8	
0.2	0.4	0.4	
0	1	1	← *classical*

Fuzzy set union (OR): $m_{A \cup B}(x) = \max(m_A(x), m_B(x))$
(the "smallest" fuzzy set containing both A and B)

Logical Operations (3)

"Green", "Blue" and "Green AND Blue"



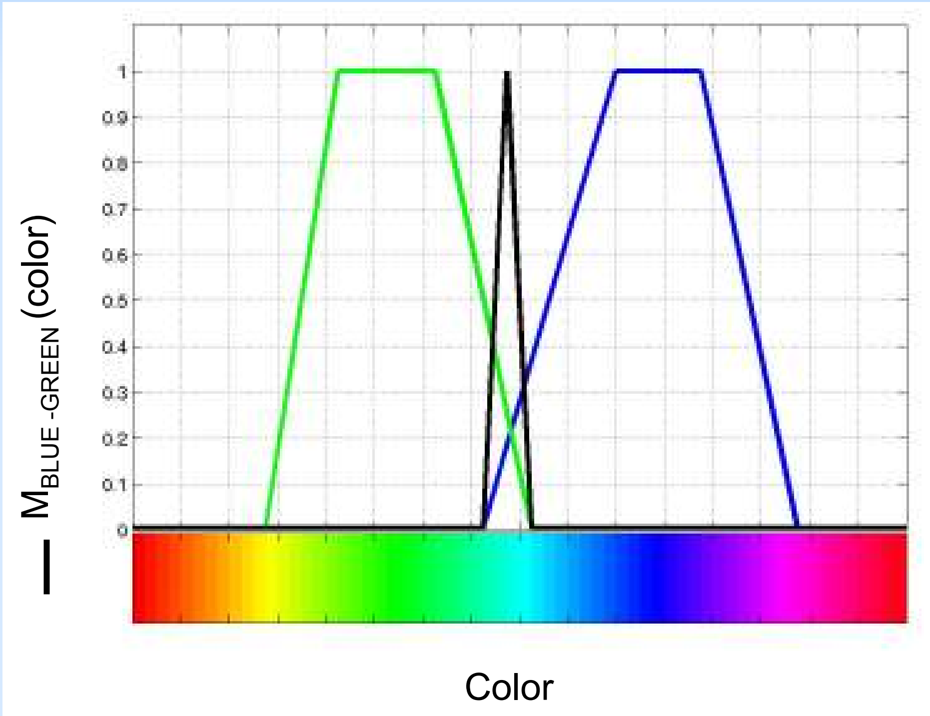
m_A	m_B	$m_{A\cap B}$	
1	1	1	← *classical*
1	0.5	0.5	
1	0	0	← *classical*
0.8	0.5	0.5	
0.5	0.8	0.5	
0.2	0.4	0.2	
0	1	0	← *classical*

Fuzzy set intersection (AND): $m_{A\cap B}(x) = \min(\, m_A(x), m_B(x)\,)$

(the "largest" fuzzy set contained in both A and B)

New Concept Formation

"Green", "Blue" and "Blue-green"

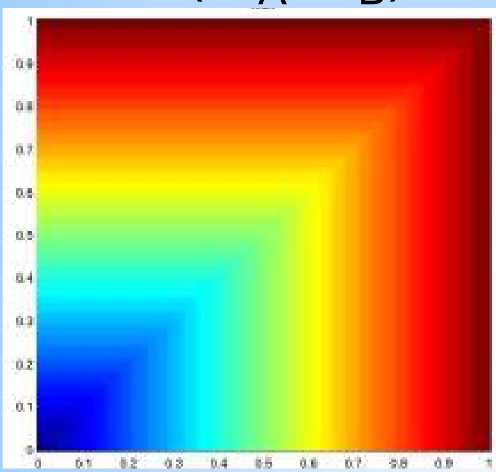


(Re-normalized intersection)

Additional Logical Operations

$\max(m_A, m_B)$

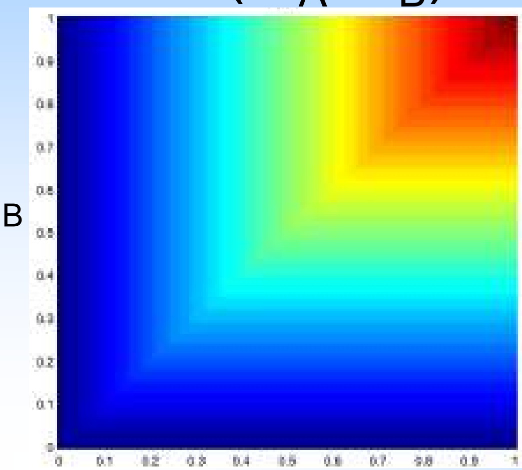
m_B



m_A

$\min(m_A, m_B)$

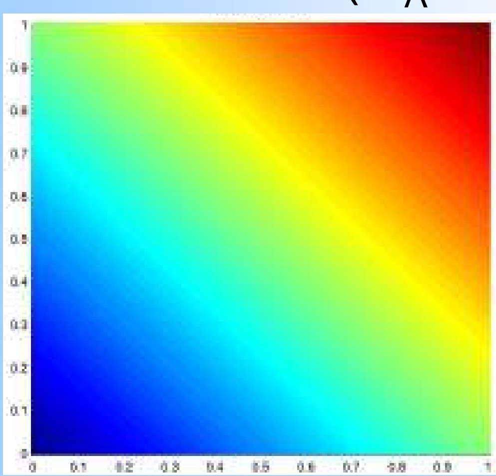
m_B



m_A

arithmetic mean: $(m_A + m_B)/2$

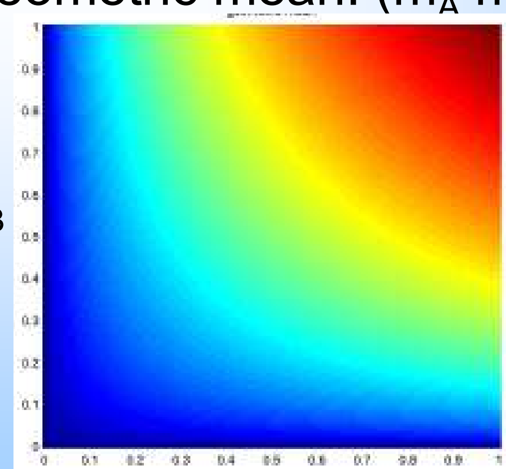
m_B



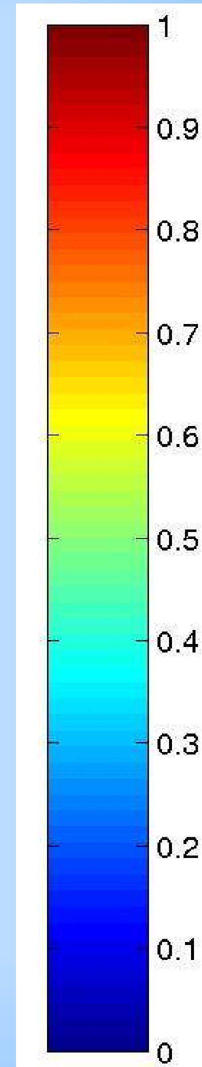
m_A

geometric mean: $(m_A \cdot m_B)^{1/2}$

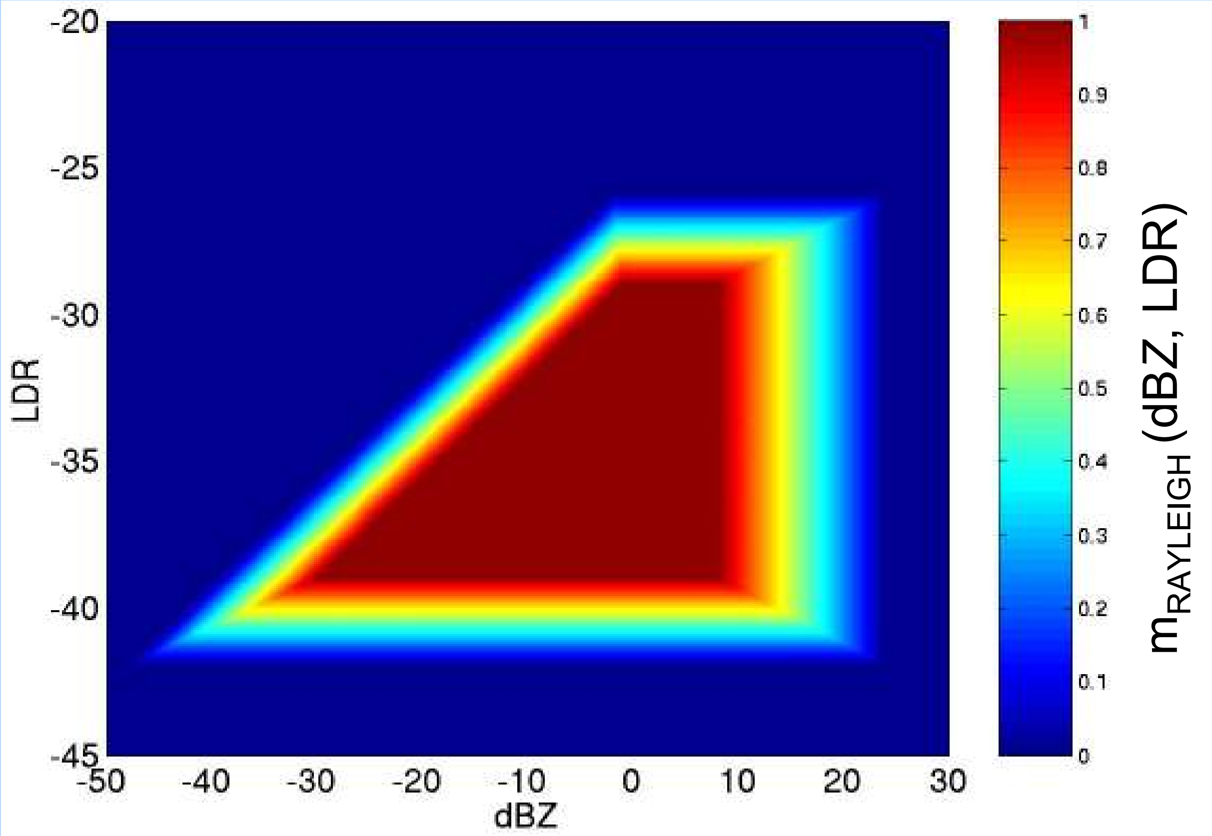
m_B



m_A



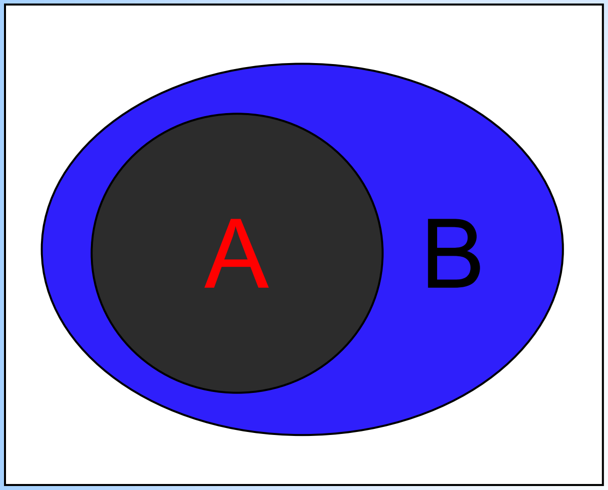
Multidimensional Membership Functions



Example: Membership value (also *interest map* or *likelihood function*) for "Rayleigh scattering conditions at W-band" as a function of radar dBZ and LDR (20° beam elevation)

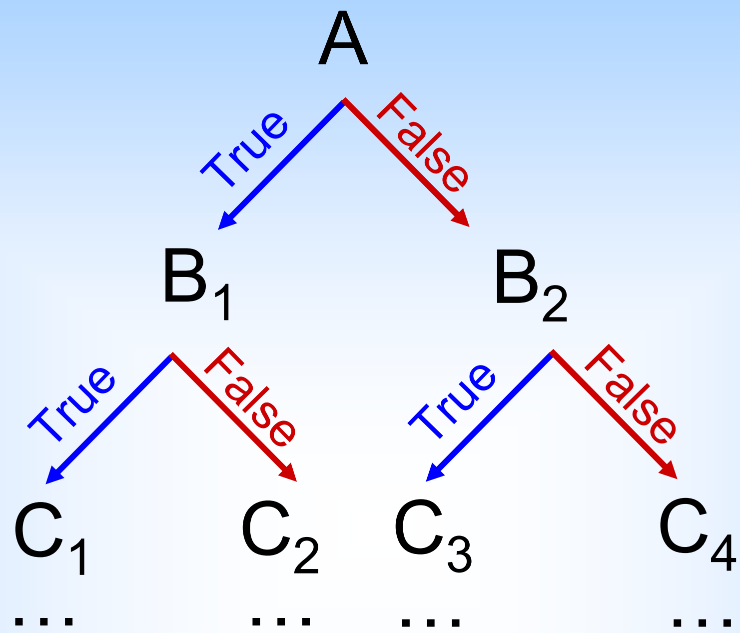
Classical Inference

- "If A then B" $\Leftrightarrow$ "$A \subset B$" $\Leftrightarrow$ "$A \cap B = A$"



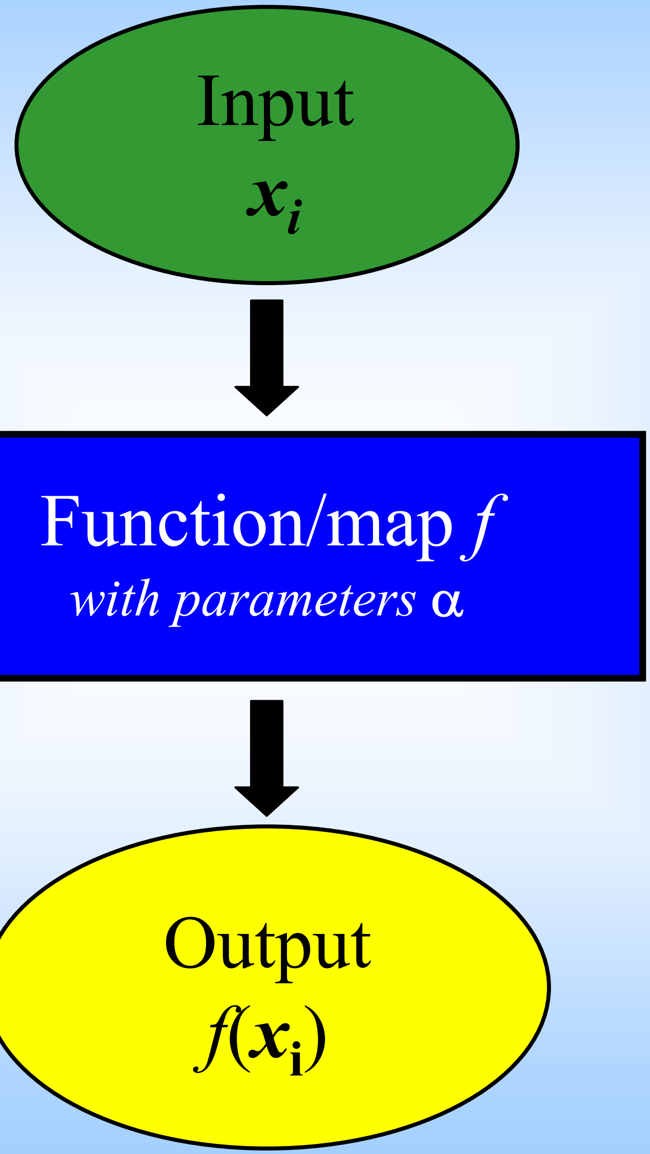
- In words: "If (in set "A" with certainty) then (in set "B" with certainty)"
- E.g., "If $\underbrace{\text{it is raining}}_{A}$, then $\underbrace{\text{it is overcast}}_{B}$."

Classical Expert System (Decision Tree)

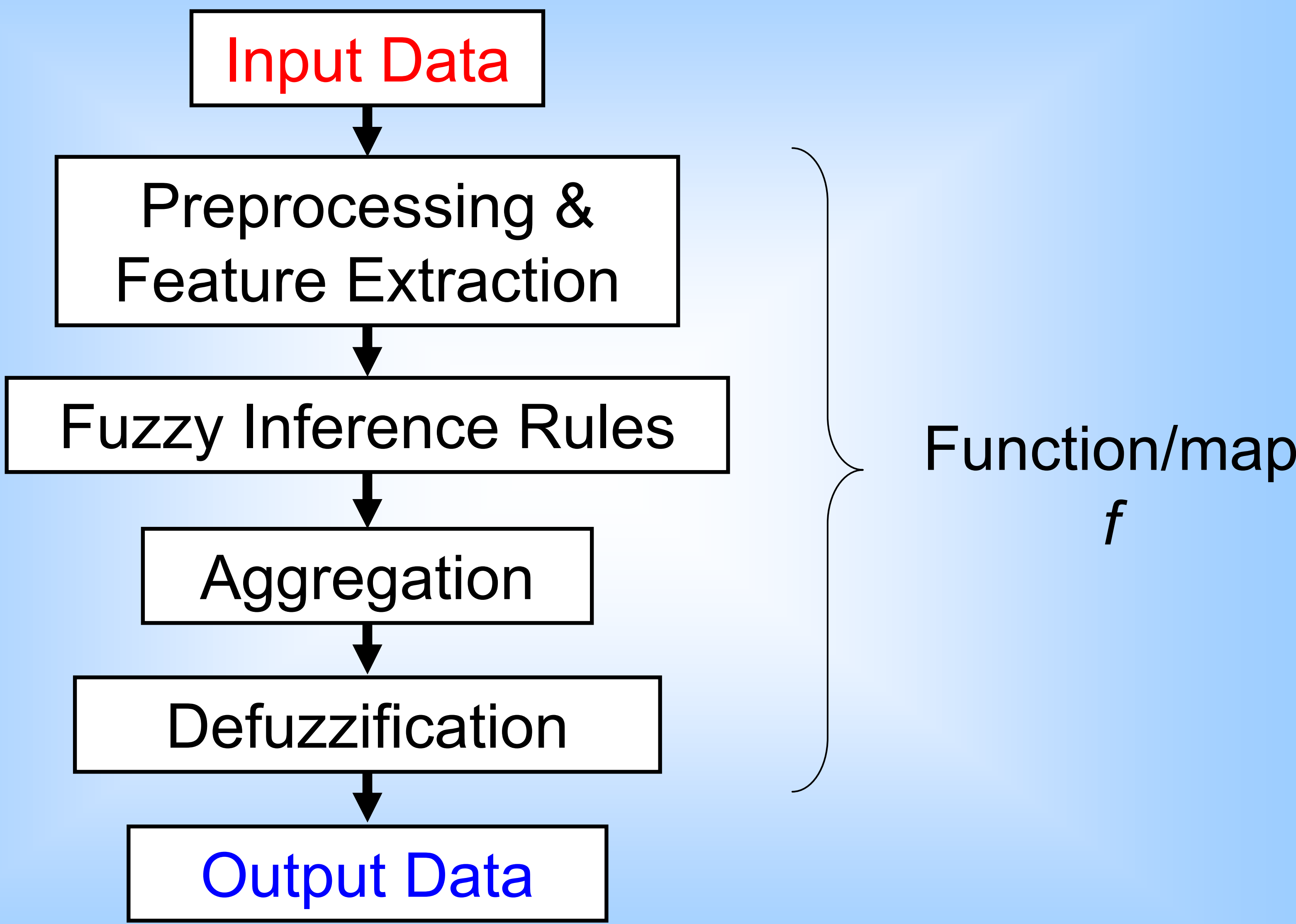


- Once a statement is evaluated true or false (e.g., threshold applied), any ambiguity is removed
- In contrast, FL attempts to retain all information until a final “defuzzification” step

Expert System



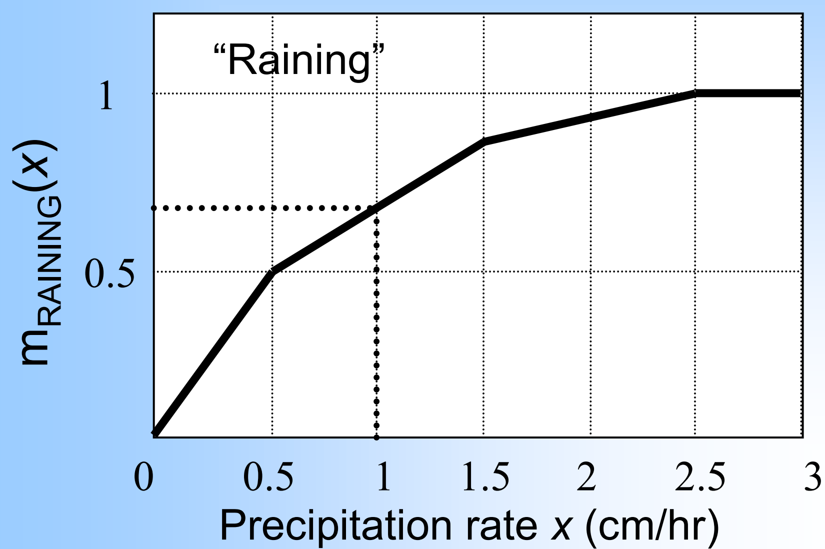
Fuzzy Expert System

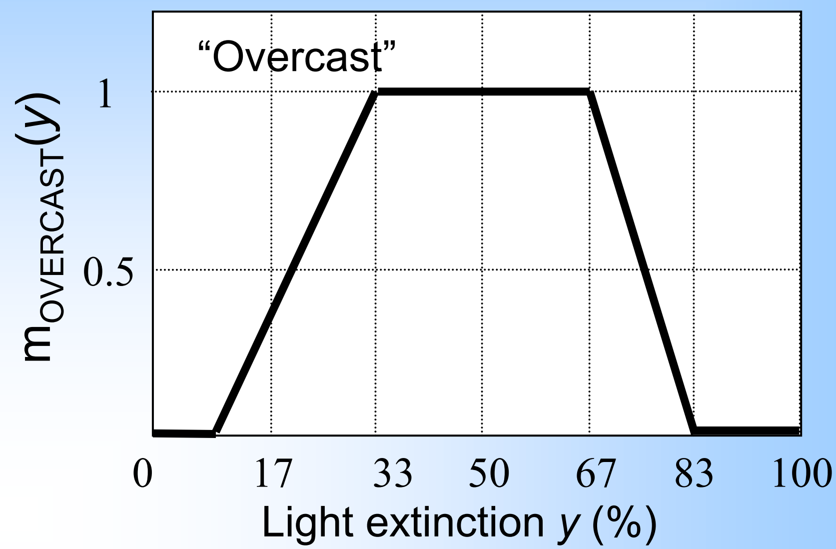


Mamdami-style Fuzzy Inference (1)

- Developed in 1975 by Ebrahim Mamdami for steam engine control using linguistic rules
- "If A then B" $\Leftrightarrow$ $m_{B|x}(y) = \min(\ m_A(x), m_B(y)\ )$ (where B|*x* denotes "B given *x*" and *y* is the target variable)
- In words: "If (*x* is "A" to the extent $m_A(x)$) then (*y* is "B" to at most the extent $m_A(x)$)"
- E.g., "If it is raining to degree *m*, then it is overcast to degree (or with belief) at most *m*."

Mamdami-style Fuzzy Inference (2)

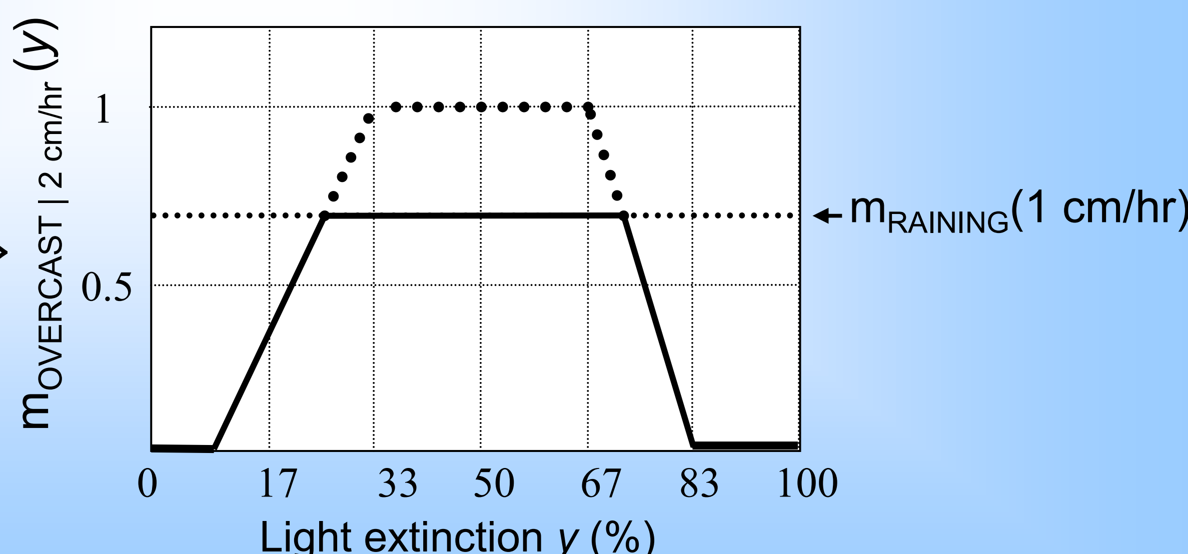




"If it is raining,

then it is overcast" ⇒

AND x = 1 cm/hr



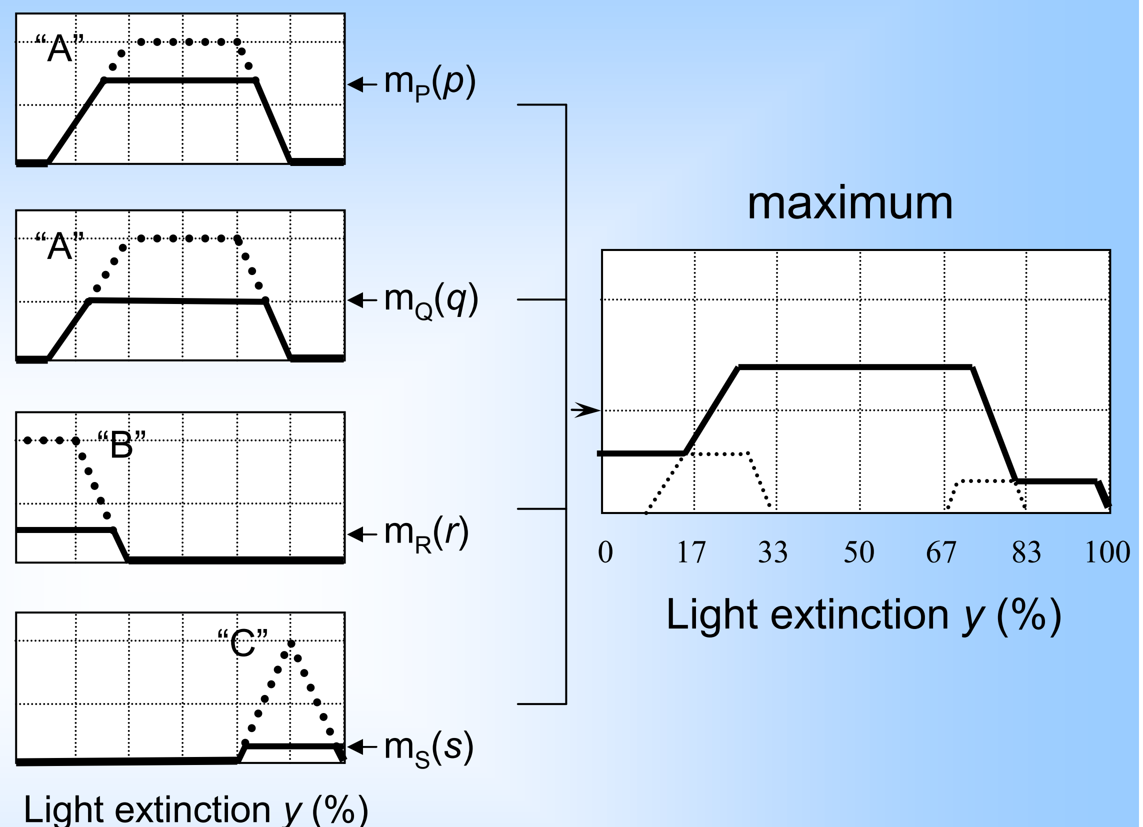
Mamdami-style Fuzzy Inference (3)

Rule 1: “P $\Rightarrow$ A” and *p*

Rule 2: “Q $\Rightarrow$ A” and *q*

Rule 3: “R $\Rightarrow$ B” and *r*

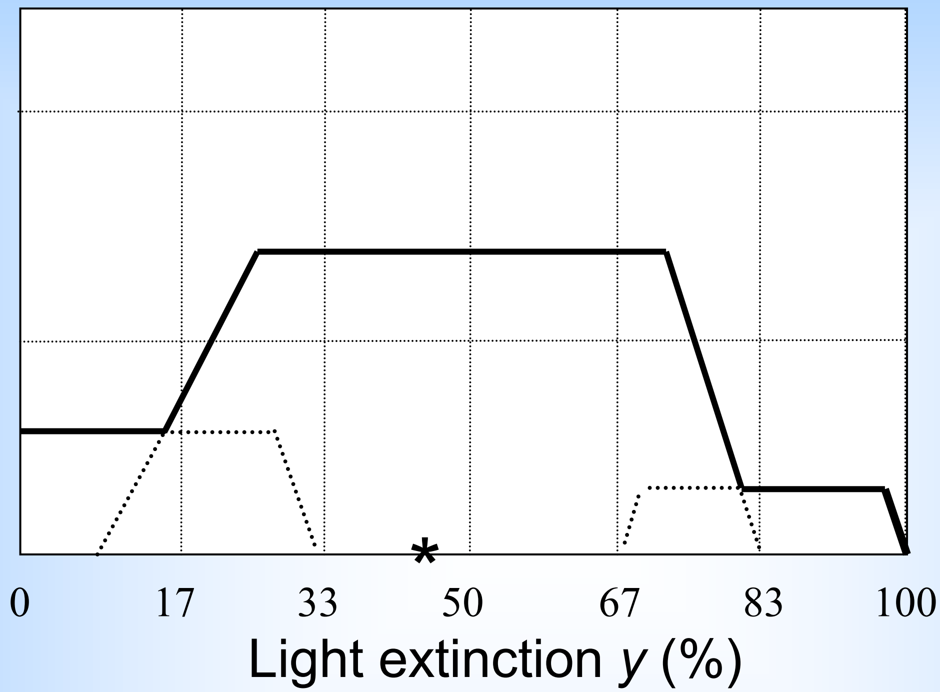
Rule 4: “S $\Rightarrow$ C” and *s*



Truncation of each conclusion based on degree of membership in premise

“Aggregation” (e.g., maximum)

Mamdami-style Fuzzy Inference (4)



Defuzzification (e.g., centroid)

$\Rightarrow$ *y* = 45% light extinction

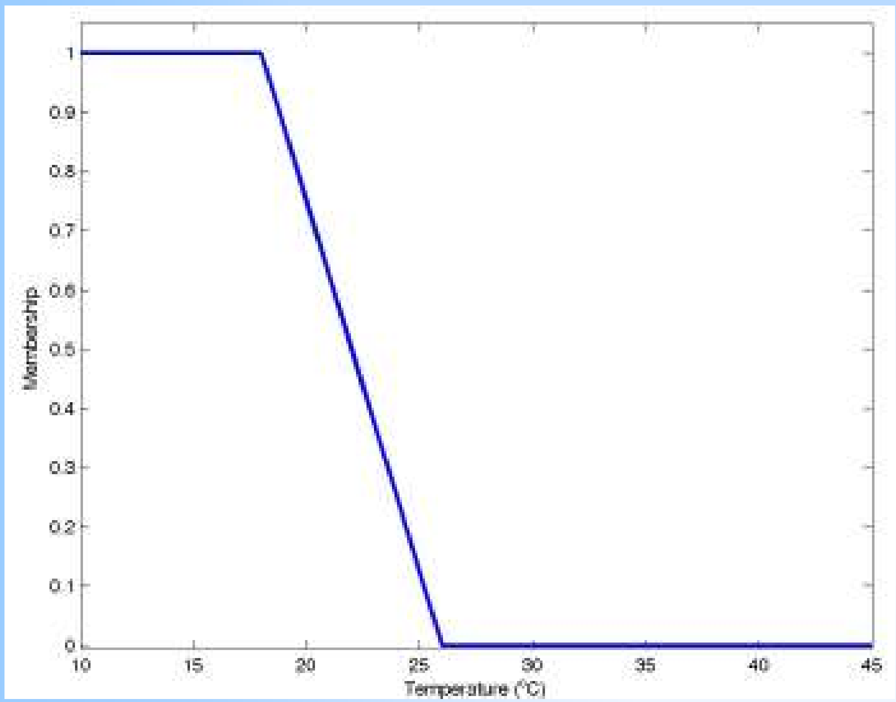
Mamdami Example (1)

- How long to water your yard on Saturday?
- Ideally, use soil sensor…but in case you don't have one, need to infer ideal time from past weather.

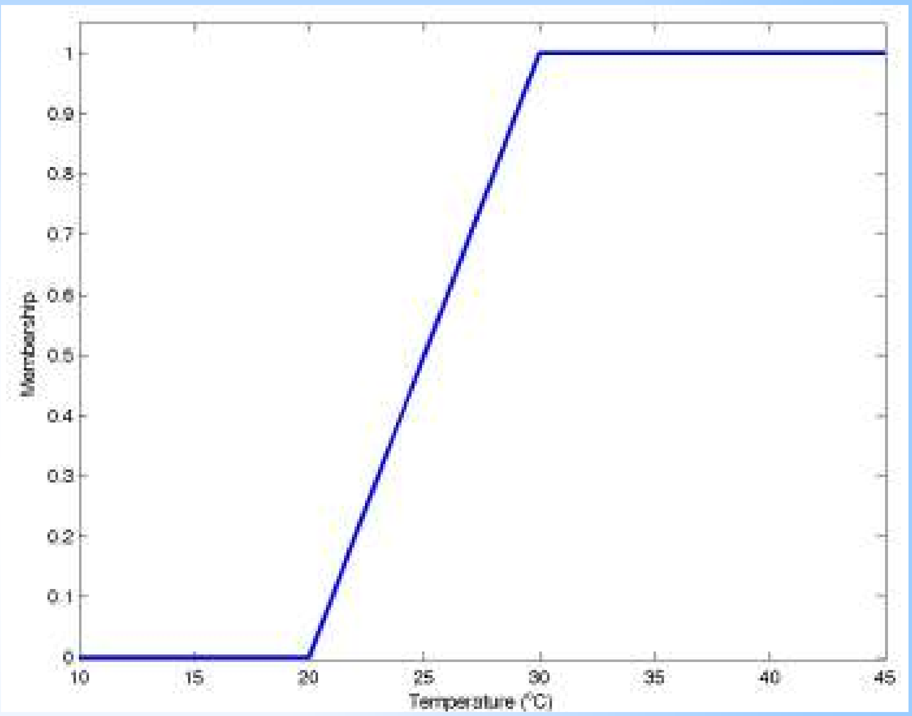
Rule 1: *If it has been cool or wet, water a little.*

Rule 2: *If it has been hot or dry, water a lot.*

Mamdami Example (2)



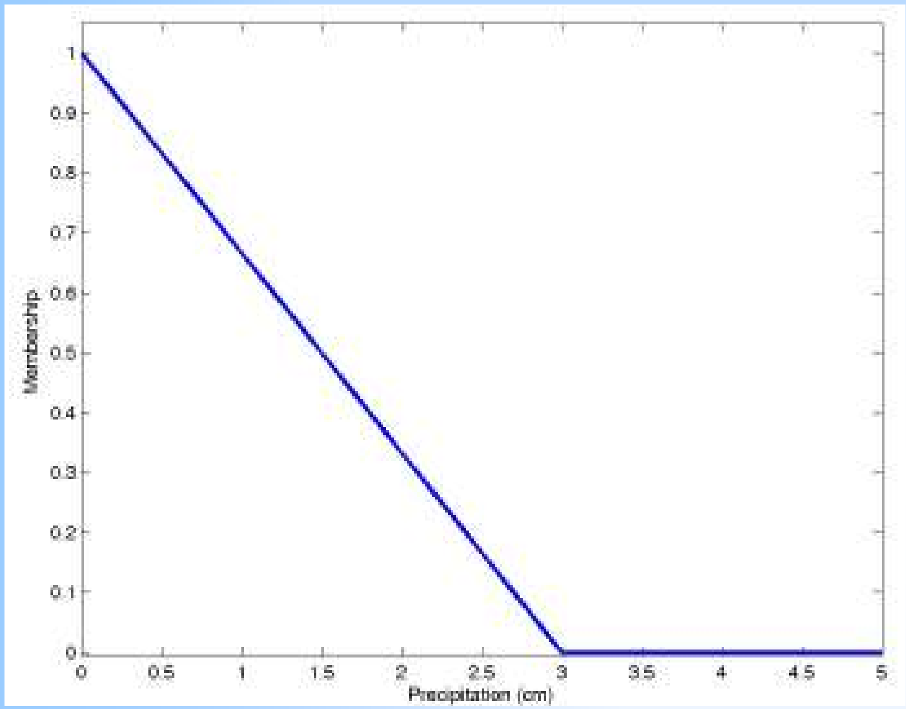
Membership function for “cool”



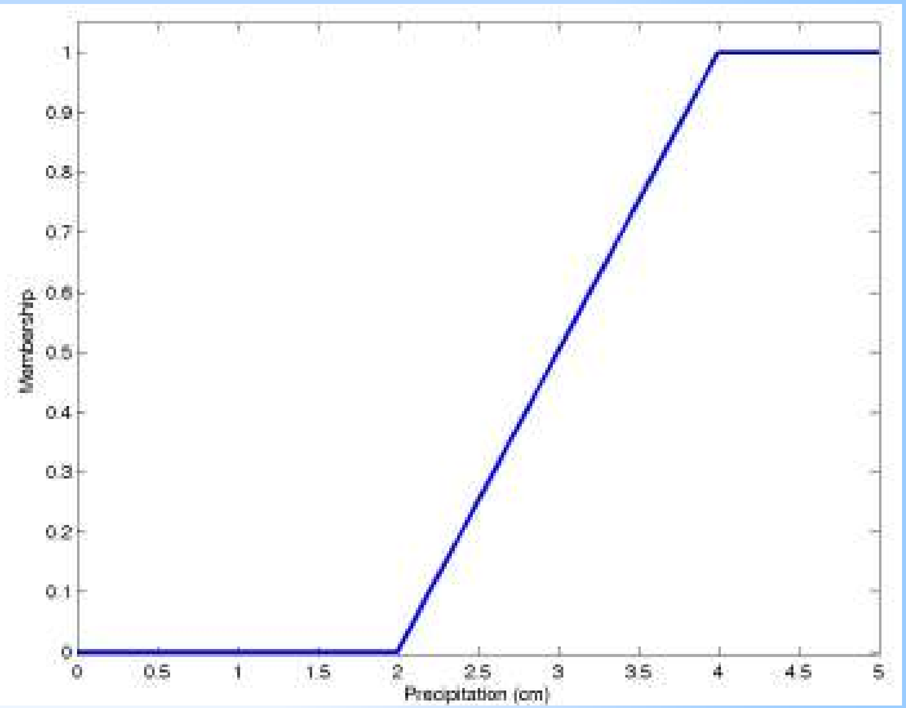
Membership function for “hot”

Temperature concepts

Mamdami Example (3)



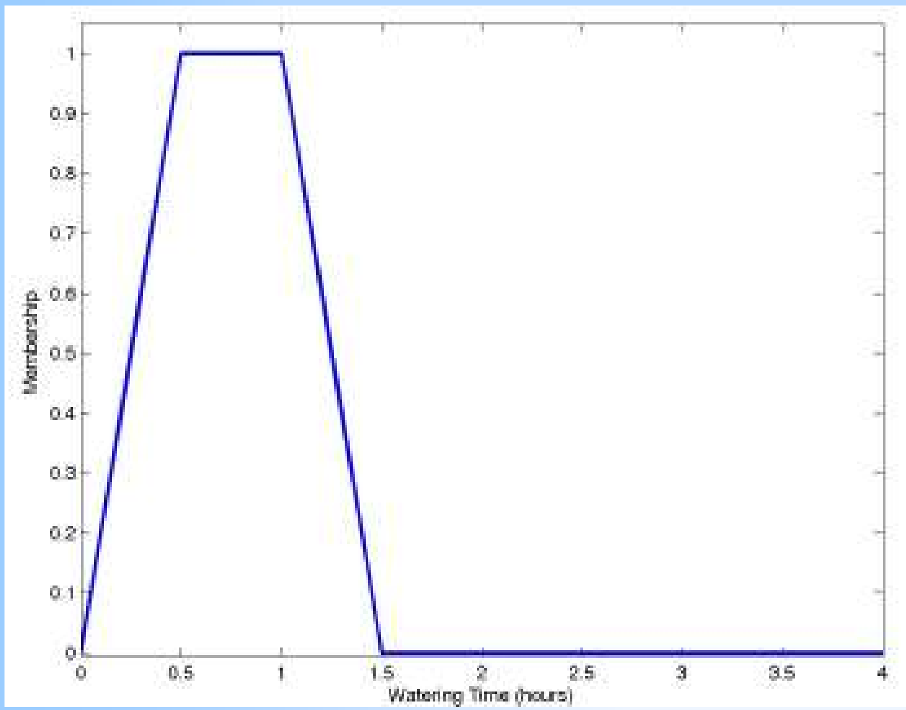
Membership function for “dry”



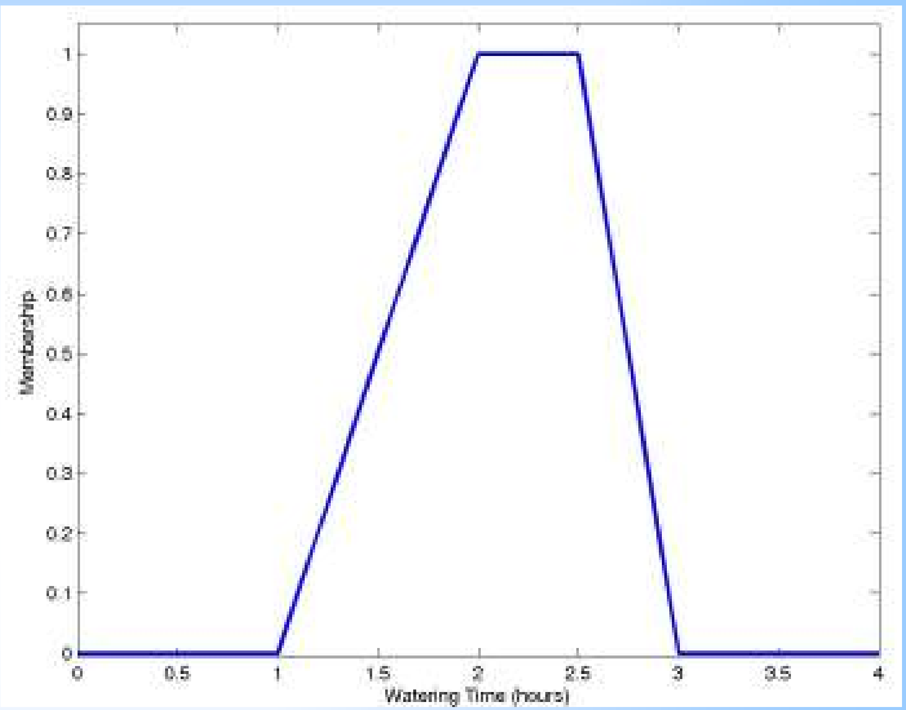
Membership function for “wet”

Precipitation concepts

Mamdami Example (4)



Membership function for “a little”

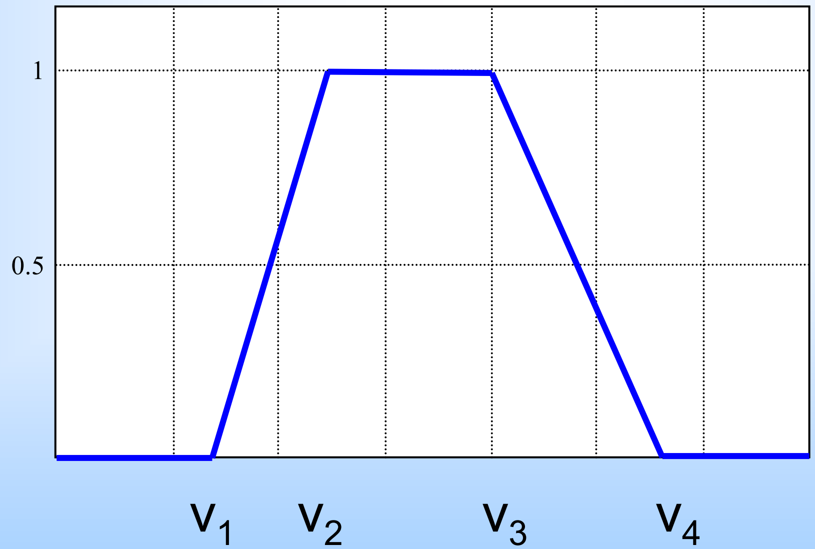


Membership function for “a lot”

Watering amount concepts

Mamdami Example (5)

```
% MEMBERSHIP Membership value for trapezoidal membership function.
%   M = MEMBERSHIP(V, X) returns the membership value M for the
%   trapezoidal membership function having vertices VERTS at input X.

function m = membership(v, x)

  v = v(:); % make v a column vector
  m = interp1([-10^99; v; 10^99],[0; 0; 1; 1; 0; 0], x);

% END (membership)
```



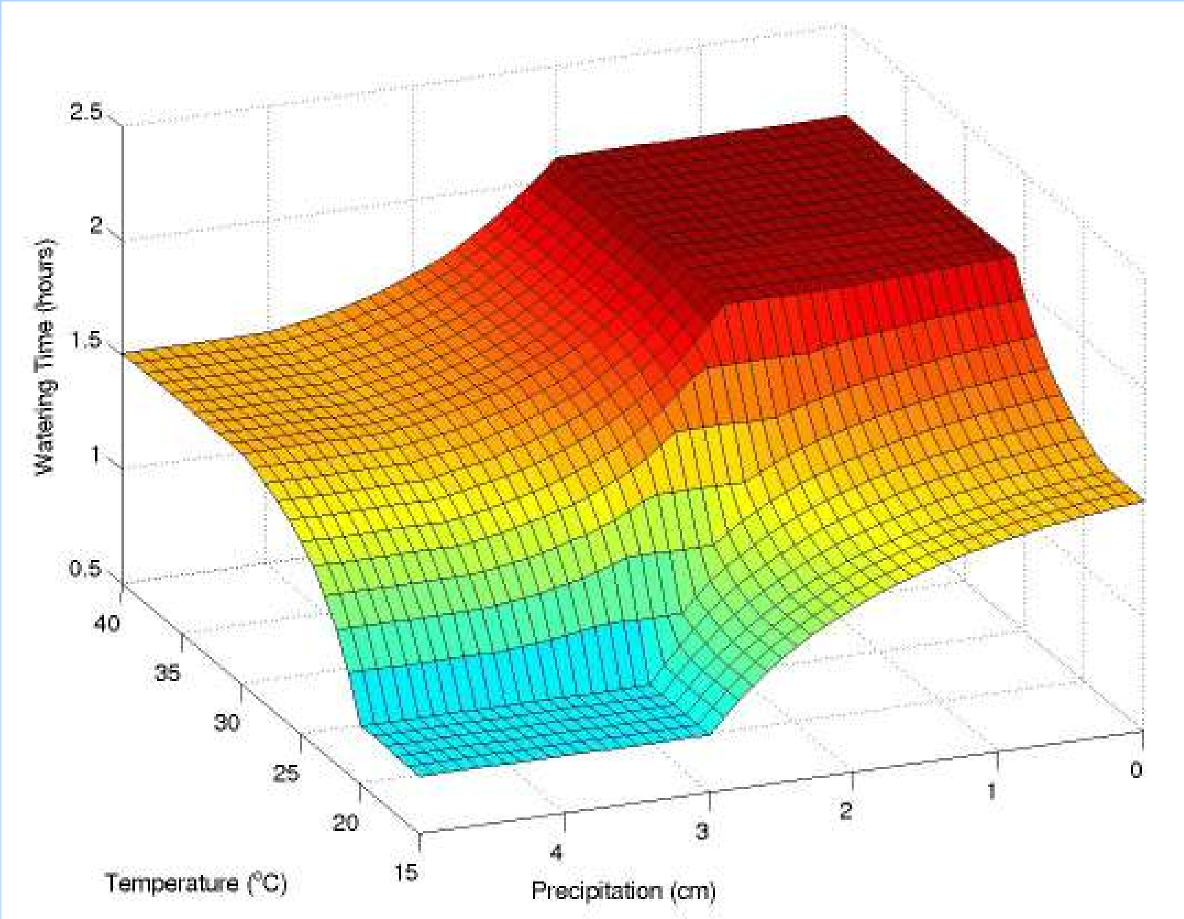
Mamdami Example (6)

```
% WATERTIMERULES Compute watering time from mean temperature (deg. C)
% and precipitation (cm) using Mamdani-style fuzzy inference.

function t = waterTimeRules(tempC,precipCm)

  % define temperature concepts via trapezoidal function vertices
  hot = [20, 30, 998, 999];
  cool = [-999, -998, 18, 26];

  % define precipitation concepts
  dry = [-999, -998, 0 3];
  wet = [2, 4, 998, 999];

  % define watering amount concepts
  alot = [1 2 2.5 3];
  alittle = [0 0.5 1 1.5];

  % perform fuzzy logic reasoning
  % 1. determine input membership values
  isHot = membership(hot,tempC);
  isCool = membership(cool,tempC);
  isDry = membership(dry, precipCm);
  isWet = membership(wet, precipCm);

. . .
```

Mamdami Example (7)

```
. . .

  % 2. perform binary operations (max == OR)
  isWetOrCool = max(isWet,isCool);
  isDryOrHot = max(isDry,isHot);

  % 3. apply rules to get fuzzy watering time set
  %      if it has been wet or cool, water alittle
  %      if it has been dry or hot, water alot
  waterVals = 0:0.1:4;
  waterTime_from_isWetOrCool = min(isWetOrCool, membership(alittle,waterVals));
  waterTime_from_isDryOrHot = min(isDryOrHot, membership(alot,waterVals));
  waterTime = max(waterTime_from_isWetOrCool, waterTime_from_isDryOrHot);

  % defuzzify by taking the centroid
  t = mean(waterTime.*waterVals)/mean(waterTime);

% END (waterTimeRules)
```

Mamdami Example (8)



Resulting Function

Takagi-Sugeno Fuzzy Inference (1)

- Developed in 1985 by Takagi, Sugeno, and Kang
- Simpler, more flexible and more computationally efficient than Mamdami-style inference
- "If ***x*** is A_1 then $z_1 = f_1(\boldsymbol{x})$"
- Aggregate *n* rules via premise-membership-weighted average of the output function values:

$$\hat{z} = \sum_{i=1}^{n} m_{A_i}(\mathbf{x})\, f_i(\mathbf{x})$$

(a "mixture of experts")

Takagi-Sugeno Fuzzy Inference (2)

- Example: "If x is A then $z = r$"

  $\Leftrightarrow$ "If x is A then $\chi_{z=r}$"

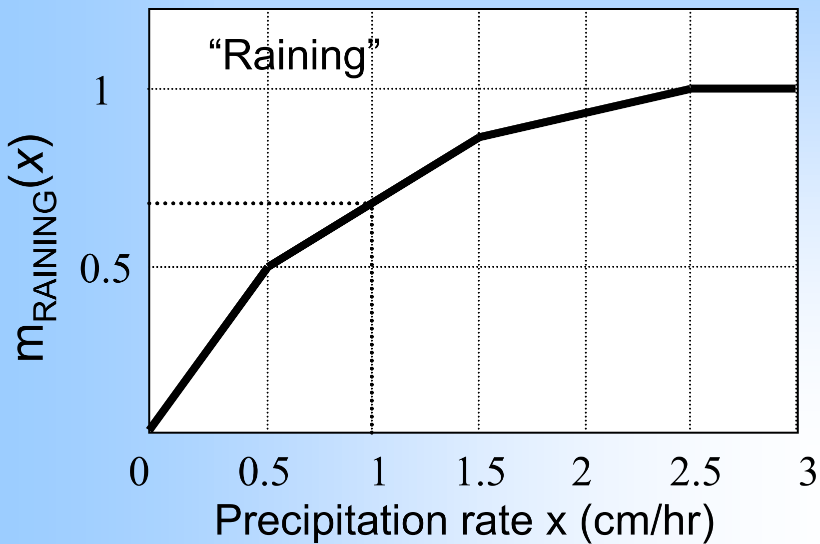
  $\Leftrightarrow$ $m_{\chi_{z=r}|x} = m_A(x)\ \chi_{z=r}$

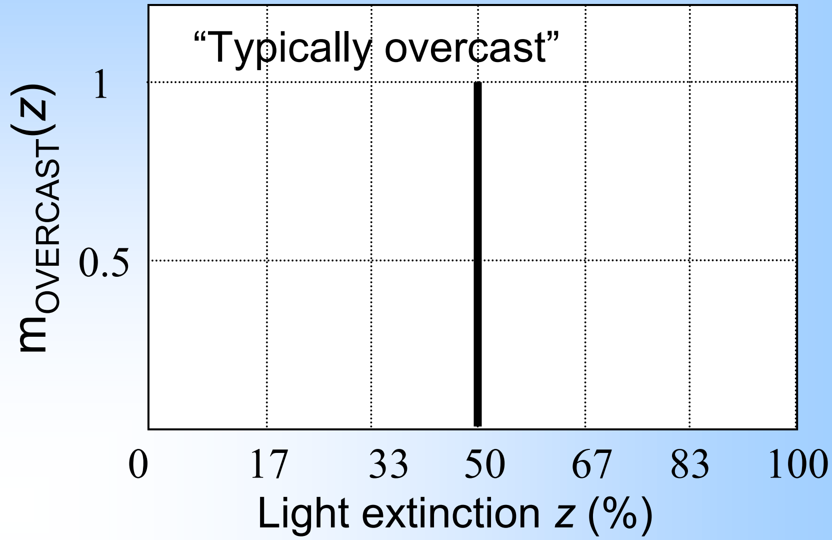
  (where $\chi_{z=r}|x$ denotes "$\chi_{z=r}$ given x")

  – In words: "If (x is "A" to the extent $m_A(x)$) then ("$z = r$" to the extent $m_A(x)$)"

  – E.g., "If it is raining to degree m, then it is "typically" overcast to degree (or with belief) at most m."

Takagi-Sugeno Fuzzy Inference (3)

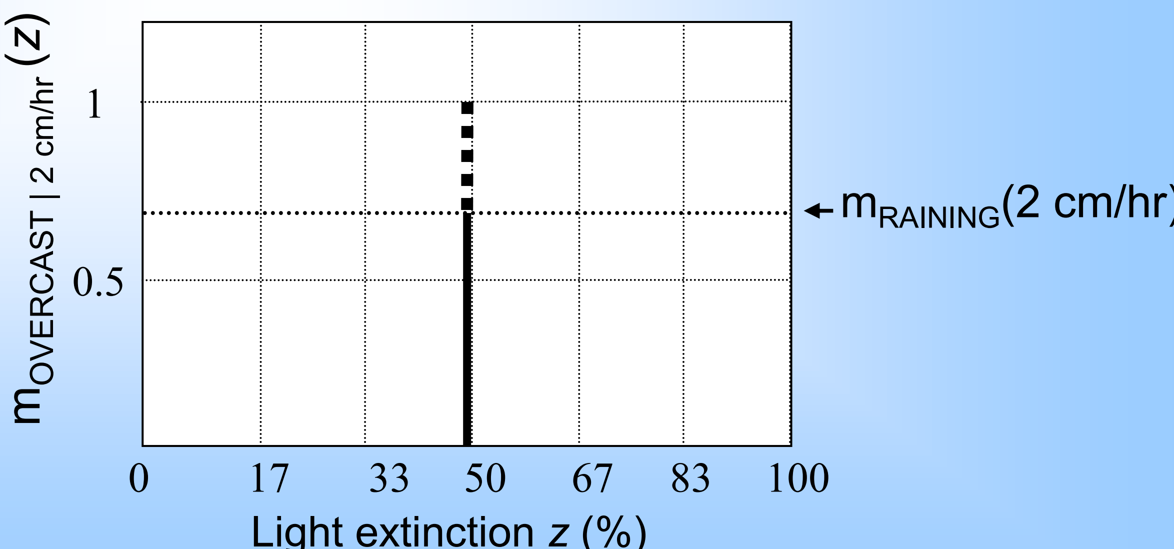




"If it is raining,

then it is overcast" $\Rightarrow$

AND x = 1 cm/hr



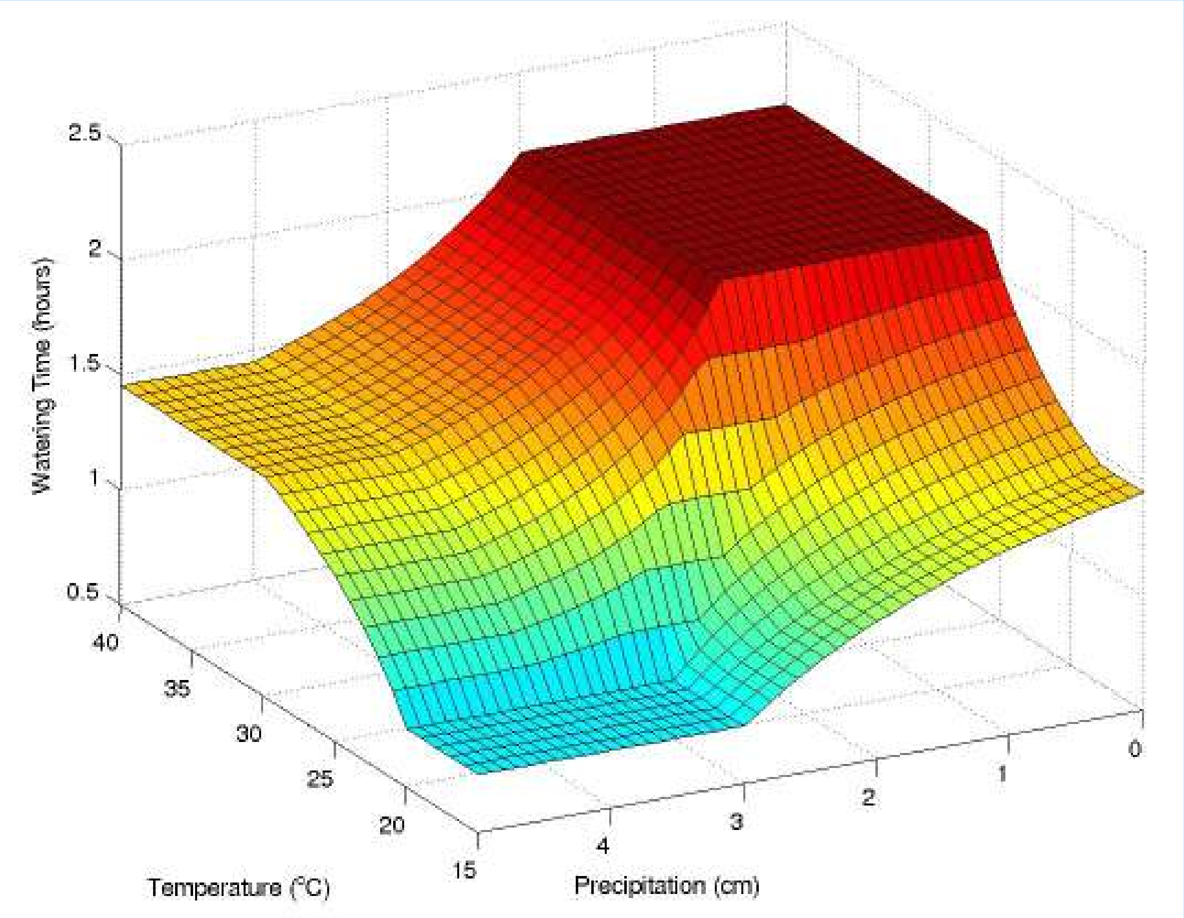
Sugeno Example (1)

```
% WATERTIMERULES2 Compute watering time from mean temperature (deg. C)
% and precipitation (cm) using Sugeno style fuzzy inference.

function t = waterTimeRules2(tempC,precipCm)

  % define temperature concepts via trapezoidal function vertices

  hot = [20, 30, 998, 999];
  cool = [-999, -998, 18, 26];

  % define precipitation concepts
  dry = [-999, -998, 0, 3];
  wet = [2, 4, 998, 999];

  % define watering amount concepts
  alotVal = 2.15;
  alittleVal = 0.75;

  % perform fuzzy logic reasoning
  % 1. determine input membership values
  isHot = membership(hot,tempC);
  isCool = membership(cool,tempC);
  isDry = membership(dry, precipCm);
  isWet = membership(wet, precipCm);

. . .
```

Sugeno Example (2)

```
                              ...

  % 2. perform binary operations
  isWetOrCool = max(isWet,isCool);
  isDryOrHot = max(isDry,isHot);

  % 3. apply rules to get watering time
  %      if it has been wet or cool, water alittle
  %      if it has been dry or hot, water alot
  t = (isWetOrCool*alittleVal + isDryOrHot*alotVal)/(isWetOrCool + isDryOrHot);

% END (waterTimeRules2)
```

Sugeno Example (3)



Resulting Function

Consensus Fuzzy Reasoning (1)

- A form of Takagi-Sugeno fuzzy inference frequently used at NCAR/RAL
- Maps inputs into prediction of the output variable (*f* is called an "interest map")
- Often, assigns data a "confidence" value between 0 and 1 (membership in the fuzzy set "input data are of good quality")
- Combines all predictions in a confidence- and importance-weighted manner to determine a final consensus prediction and (optionally) confidence

Consensus Fuzzy Reasoning (2)

evid. E_1 (conf c_1) $\xrightarrow{f_1}$ prediction P_1 (wt. w_1)

evid. E_2 (conf c_2) $\xrightarrow{f_2}$ prediction P_2 (wt. w_2)

. . .

evid. E_n (conf c_n) $\xrightarrow{f_n}$ prediction P_n (wt. w_n)

$$P = \frac{\sum_{k=1}^{n} c_k w_k P_k}{\sum_{k=1}^{n} c_k w_k}$$

or

$$P = \prod_{k=1}^{n} p_k^{\,c_k w_k / \sum_{k=1}^{n} c_k w_k}$$

evidence = raw measurement or derived feature

confidence = reliability of evidence

interest maps

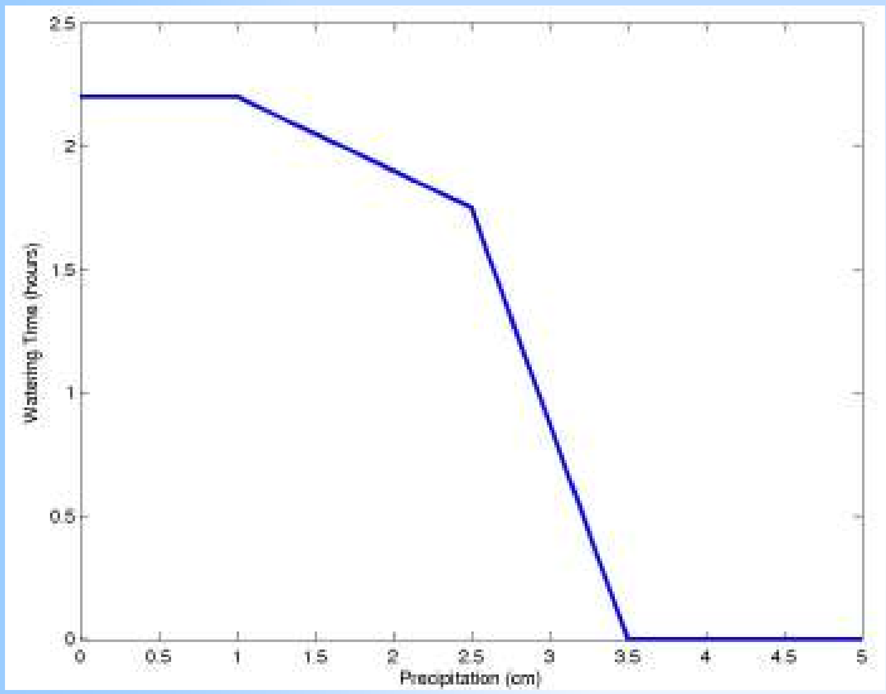
prediction = estimate of variable of interest

weight = relative strength of implication

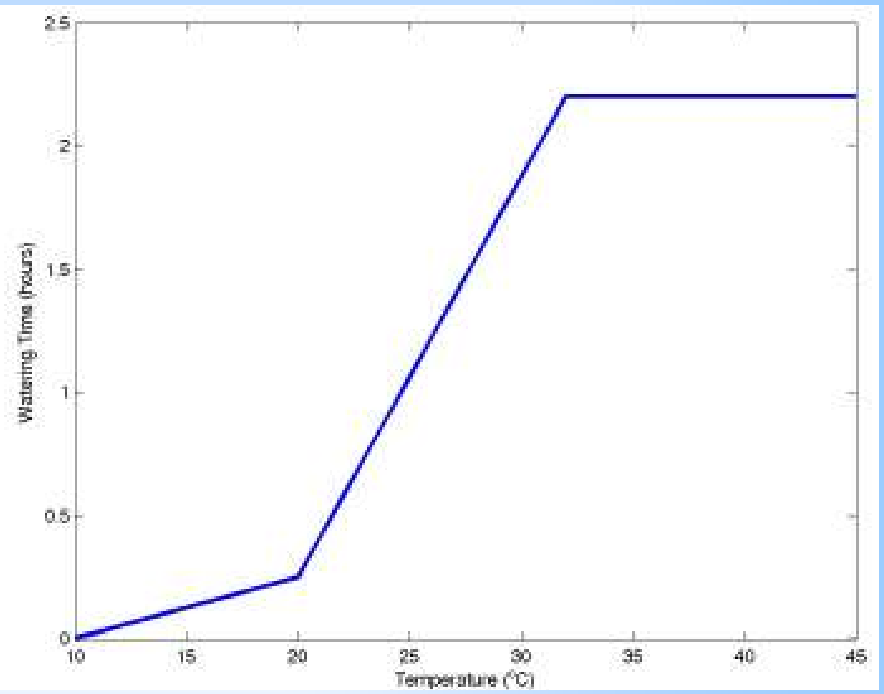
Aggregation

(e.g., weighted mean) gives consensus prediction

Consensus Example (1)



Watering interest map for precipitation

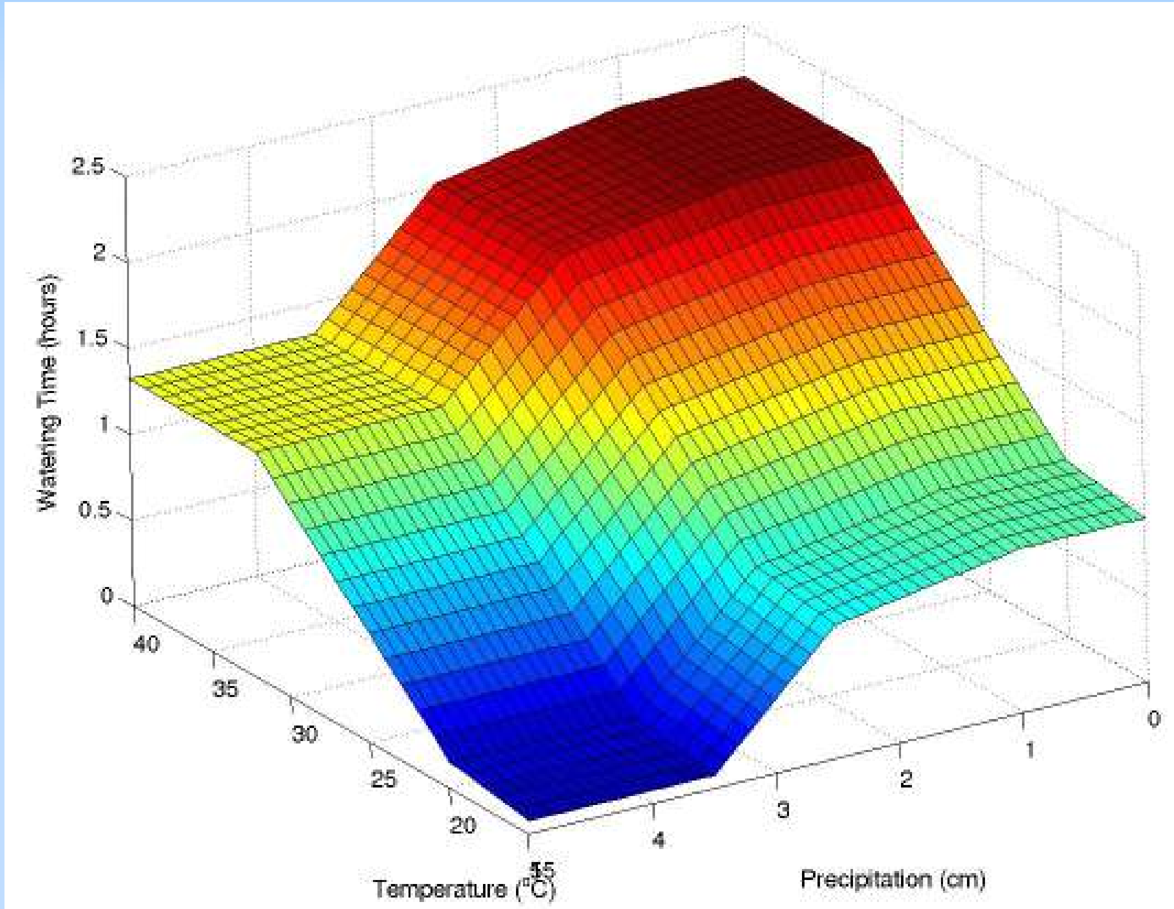


Watering interest map for temperature

Consensus Example (2)

```
% WATERTIMERULES3 WATERTIMERULES3 Compute watering time from mean temperature
% (deg. C) and preciptation (cm) using consensus fuzzy reasoning

function t = waterTimeRules3(tempC, precipCm, tempConf, precipConf)

  % diagnose watering time separately for temperature and precipitation
  tempWaterTime = interp1([-999, 10, 20, 32, 999], ...
                          [0, 0, .25, 2.2, 2.2], tempC);
  precipWaterTime = interp1([-999, 1, 2.5, 3.5, 999], ...
                            [2.2, 2.2, 1.75, 0, 0], precipCm);

  % assign weights to each
  tempWt = 0.6;
  precipWt = 0.4;

  % take a weighted average to get the "consensus" time
  t = (tempConf*tempWt*tempWaterTime + precipConf*precipWt*precipWaterTime)./ ...
      (tempConf*tempWt + precipConf*precipWt);

% END (waterTimeRules3)
```

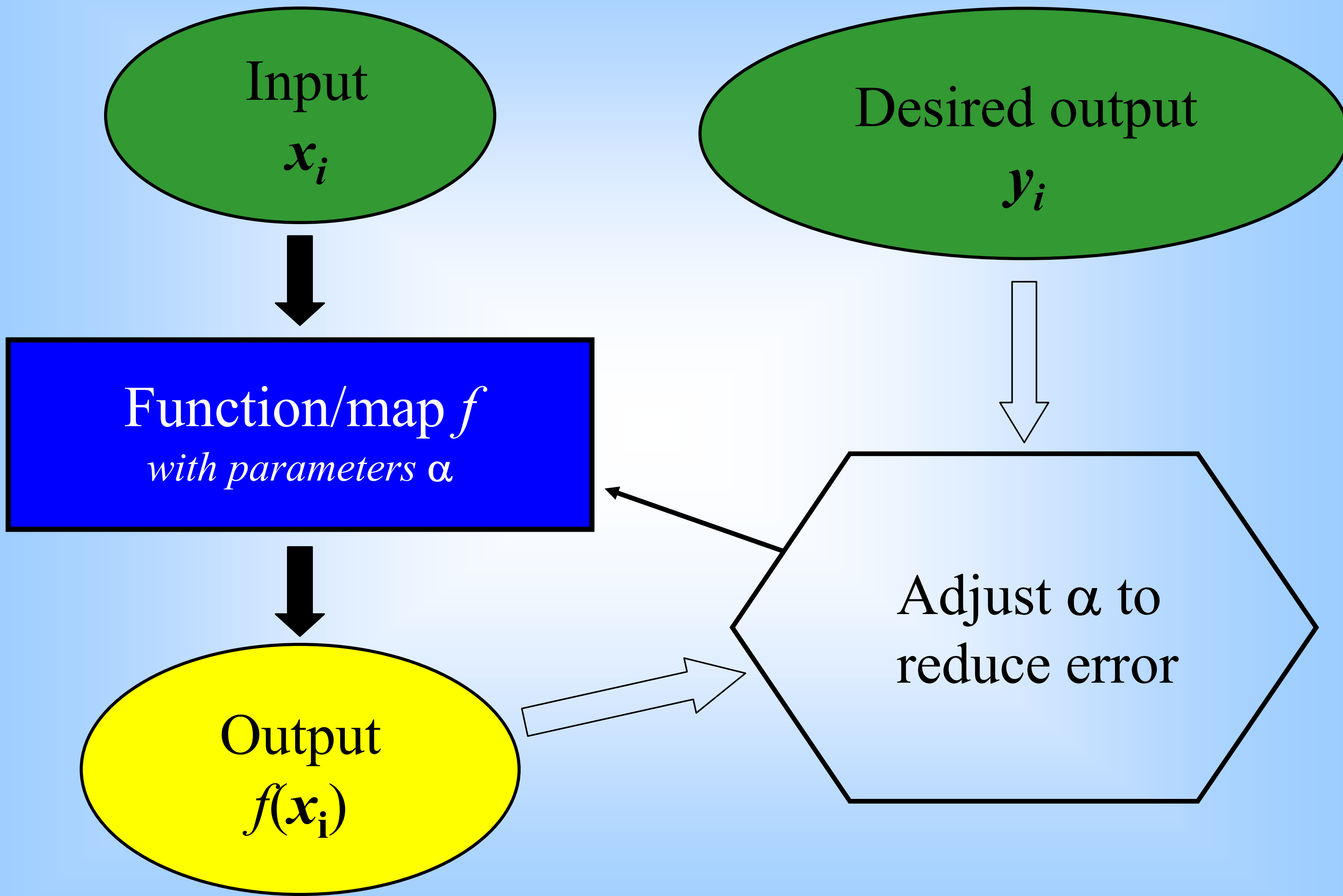
Consensus Example (3)



Resulting Function

(tempConf = precipConf = 1)

Fuzzy Logic Tuning (1)

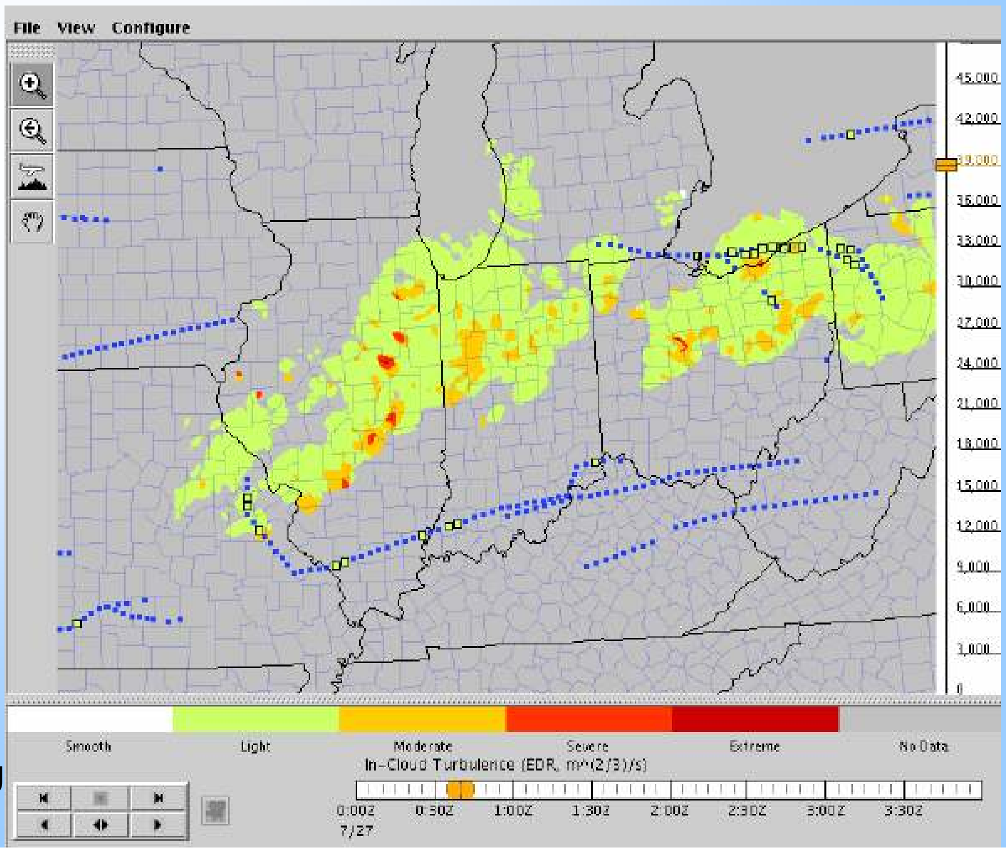


Fuzzy Logic Tuning (2)

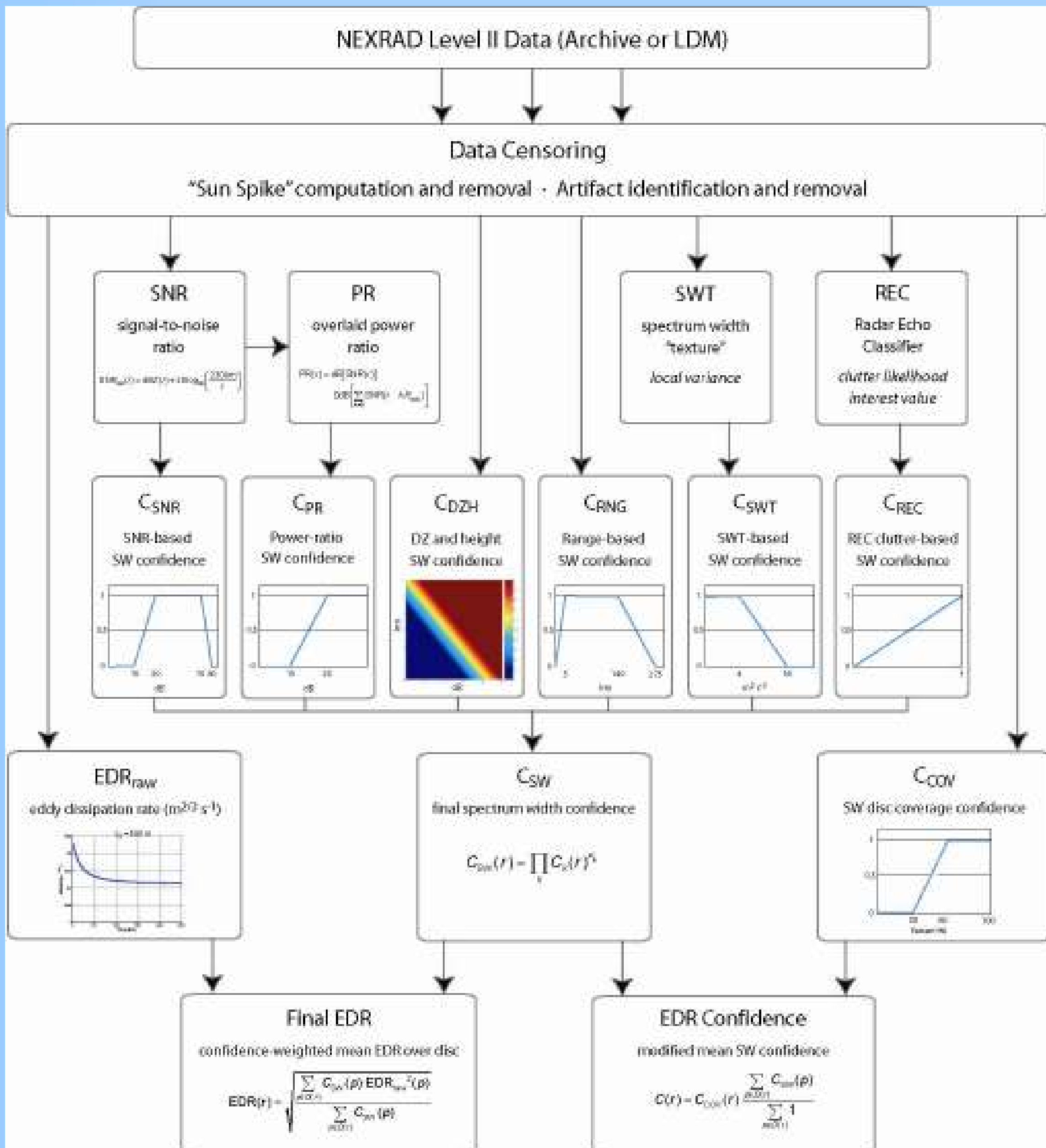
- What error function?
  - Mean squared error
  - Area under ROC curve
  - Model that represents cost of errors in an operational system
- What method for tuning?
  - Gradient descent (Neural network style backpropagation $\rightarrow$ Neuro-Fuzzy systems)
  - Genetic Algorithms
  - Any optimization method that works!

Fuzzy Logic Tuning Example

- NCAR Turbulence Detection Algorithm (NTDA)
- Uses weather radar reflectivity, radial velocity, and spectrum width to perform quality control and produce estimates of eddy dissipation rate (EDR), a turbulence metric
- Can be compared to aircraft *in situ* EDR reports for tuning ⟶



Fuzzy Logic Tuning Example (NTDA)



Input Data

$$f(v_1, v_2, \ldots, \\ r_1, r_2, \ldots, \\ p_1, p_2, \ldots)$$

Output Data

Adaptive Fuzzy Systems

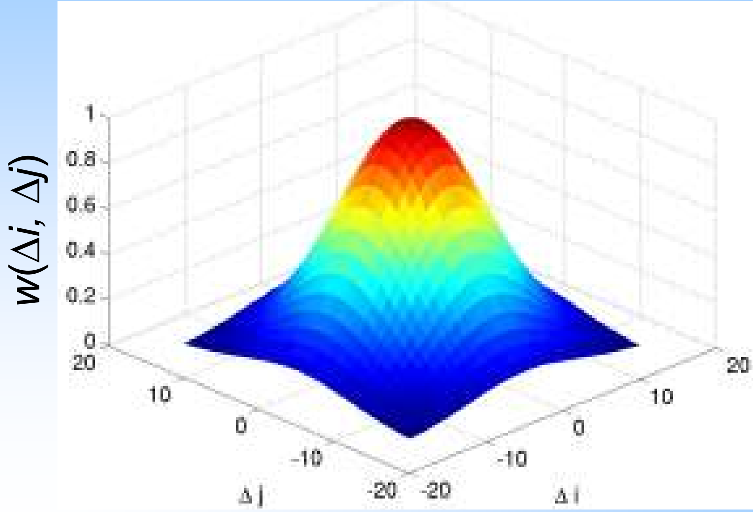
- Modify system parameters to optimize performance or adjust to changing conditions "online"
- E.g., for fuzzy consensus system, use gradient descent method to update weights based on observed error.

$$P = \frac{\sum_{k=1}^{n} c_k w_k \, P_k}{\sum_{k=1}^{n} c_k w_k}$$

Update the w_k based on ongoing performance

Fuzzy Trimmed-Mean Kernel Smoothing

- Suppose *w*(Δ*i*, Δ*j*) is a kernel function,→ *Z* are data and *c* are confidences



- For every index pair *i, j*
  - Sort $\left\{ Z(i.j) :- m \leq i \leq m, - n \leq j \leq n \right\}$
  - Set extreme *p*% of the corresponding sorted *w*(Δ*i*, Δ*j*) *c*(*i*+Δ*i*, *j*+Δ*j*) to 0
  - Compute

$$\bar{Z}(i,j) = \frac{\sum_{\Delta i=-m}^{m} \sum_{\Delta j=-n}^{n} w(\Delta i, \Delta j)\, c(i+\Delta i, j+\Delta j)\, Z(i+\Delta i, j+\Delta j)}{\sum_{\Delta i=-m}^{m} \sum_{\Delta j=-n}^{n} w(\Delta i, \Delta j)\, c(i+\Delta i, j+\Delta j)}$$

What if no expert is available?

- Use data mining (e.g., random forests) to determine what variables or derived features are important for the desired prediction.
- Use a combination of fuzzy clustering and in-cluster regression to create a Takagi-Sugeno style inference system, or build a Mamdami system with a “reasonable” form.
- Use a genetic algorithm to optimize the algorithm parameters relative to the desired performance metric.

Summary of FL Theory/Philosophy: *Exploit Ambiguity*!

- Fuzzy Logic provides a tool for modeling human reasoning involving “unsharp” concepts, allowing common-sense AI solutions to be produced quickly and at low cost.
- Data mining (machine learning) techniques can be used to discover relationships in data that can help inform the development of FL algorithms.
- Fuzzy logic algorithms can be “tuned” to optimize performance using machine learning techniques.

Research Applications Laboratory

- Laboratory within NCAR, comprised of five programs
  - Aviation Applications
  - Hydrometeorology
  - National Security
  - Weather Systems and Assessment
  - Joint Numerical Testbed
- Technology transfer for NCAR, plus some basic research

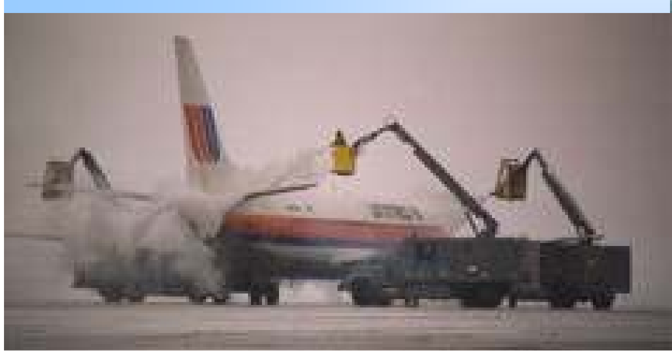
Acknowledgement: Cathy Kessinger created many of the following slides.

Applications of FL in RAL

- Summer and winter storms
  - Continental and oceanic
  - Cloud scale to synoptic scale
- Full range of meteorological instruments
- Numerical models
- Sensor data fusion
- Decision support systems



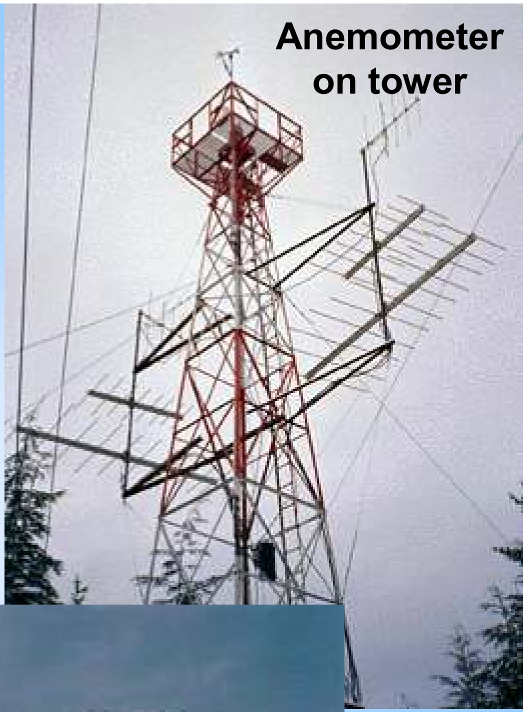




Categories of Algorithms

- Improving data quality
  - Radar Echo Classifier (REC) for Doppler radars
  - NCAR Improved Moment Algorithm (NIMA) for profilers
  - Intelligent Outlier Detection Algorithm (IODA) for timeseries data
- Detection/diagnosis of current weather phenomena
  - Microburst Automatic Detection (MAD) using Doppler radar data
  - Particle classification using S-Band polarization radar measurements
  - Current Icing Potential (CIP)
- Forecasting weather phenomena
  - Thunderstorm AutoNowcast System (ANC)
  - Graphical Turbulence Guidance (GTG) algorithm

Algorithms for Improving Data Quality



Radar Echo Classifier (REC) for NEXRAD

Brownsville, TX WSR-88D

Radar Echo Classifier

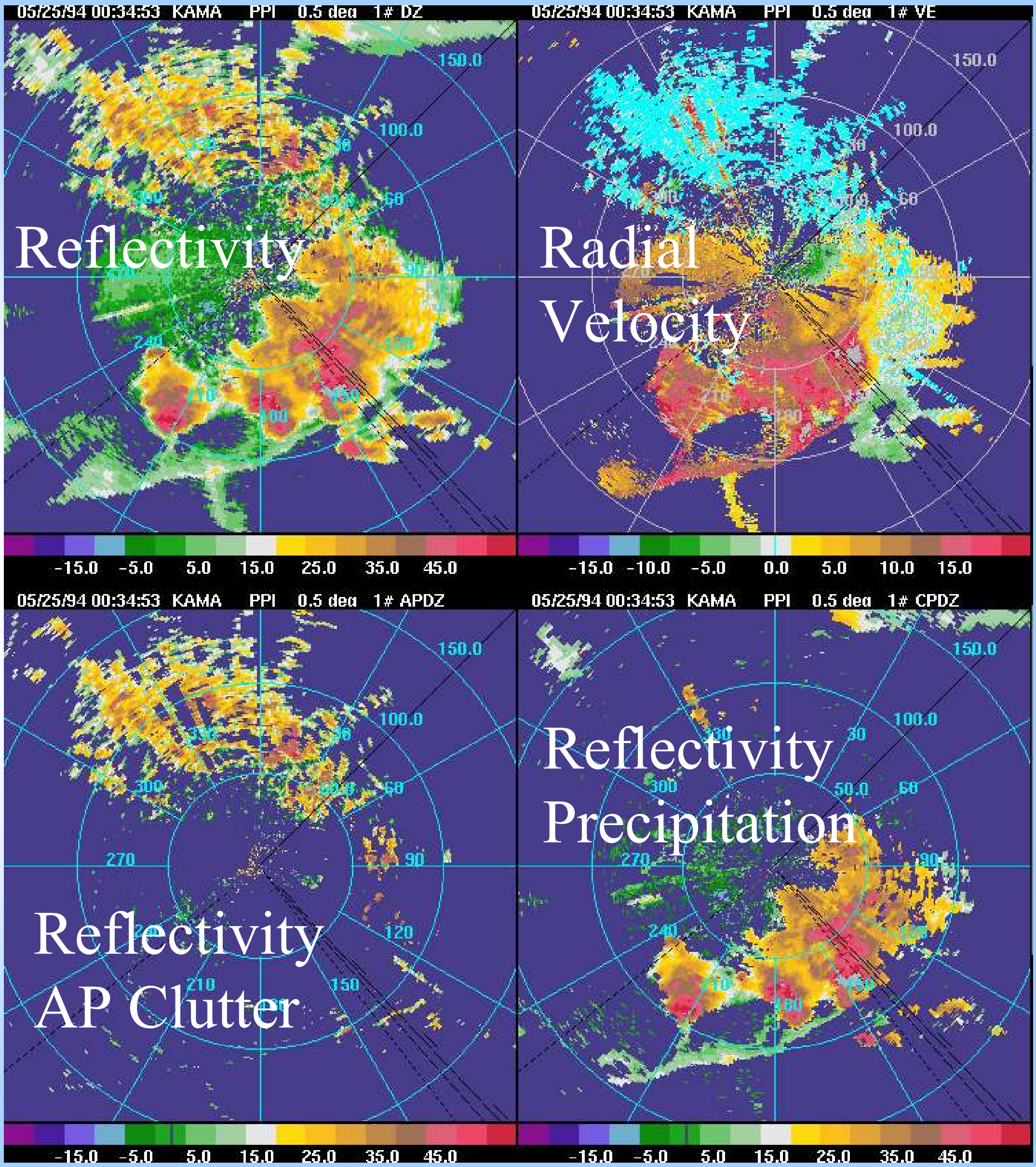
- Consists of four algorithms
  - Anomalously propagated (AP) ground clutter detection algorithm (APDA)
  - Precipitation detection algorithm (PDA)
  - Sea clutter detection algorithm (SCDA)
  - Insect clear air detection algorithm (ICADA)

- The APDA is operational on all NEXRADs
  - Used for quality control (ground clutter removal) in radar-derived rainfall algorithm

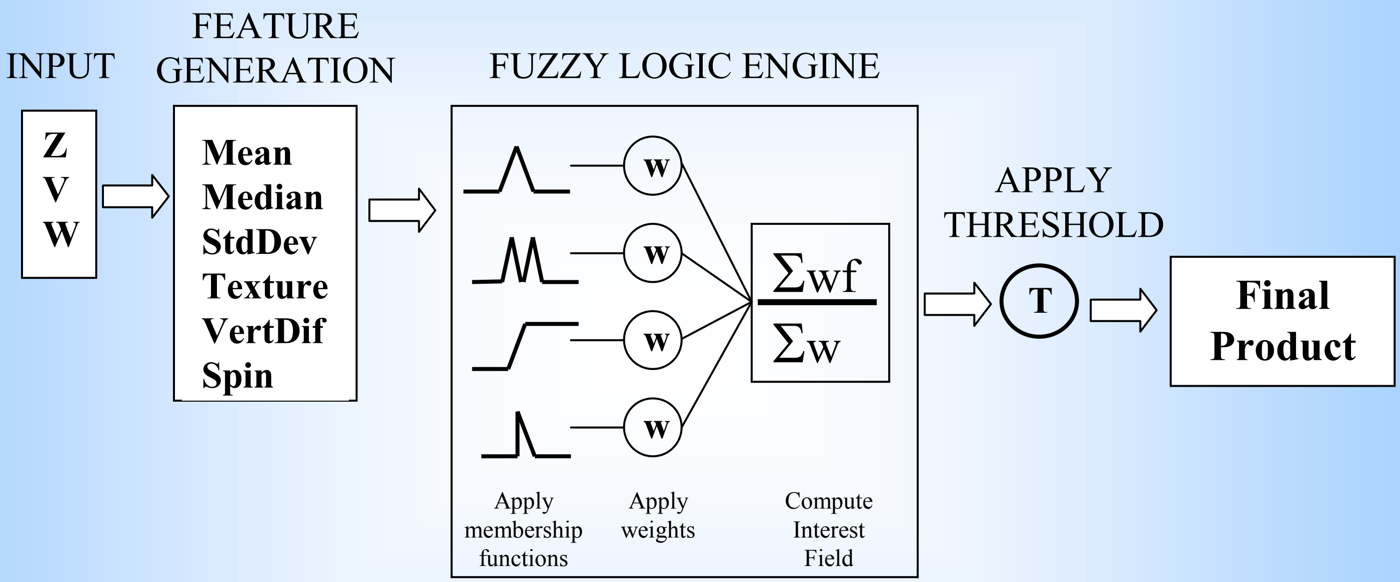
NEXRAD data contaminated with ground clutter

Ground clutter creates errors in radar-derived rainfall

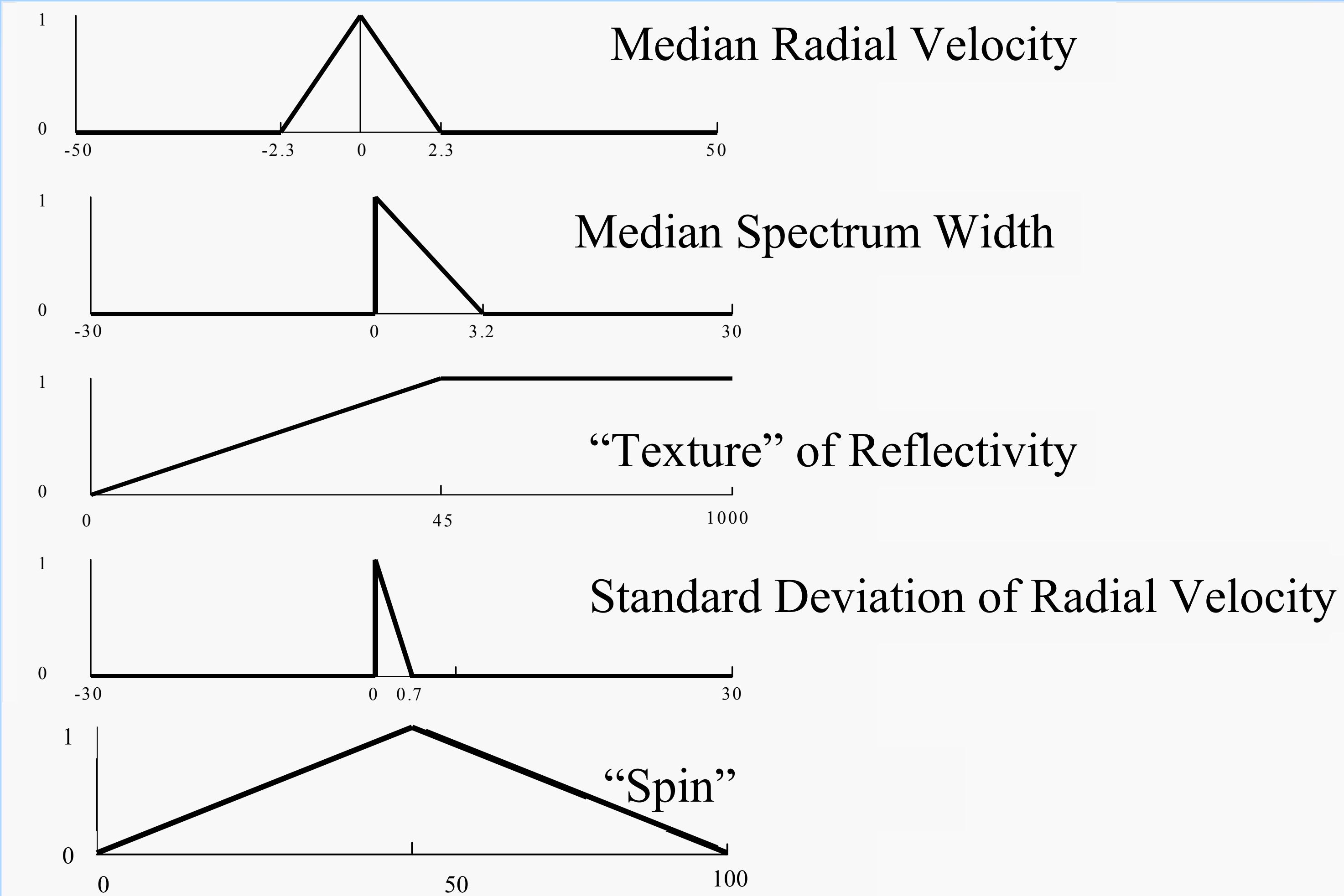
Goal of REC is to identify and separate clutter return from precipitation return



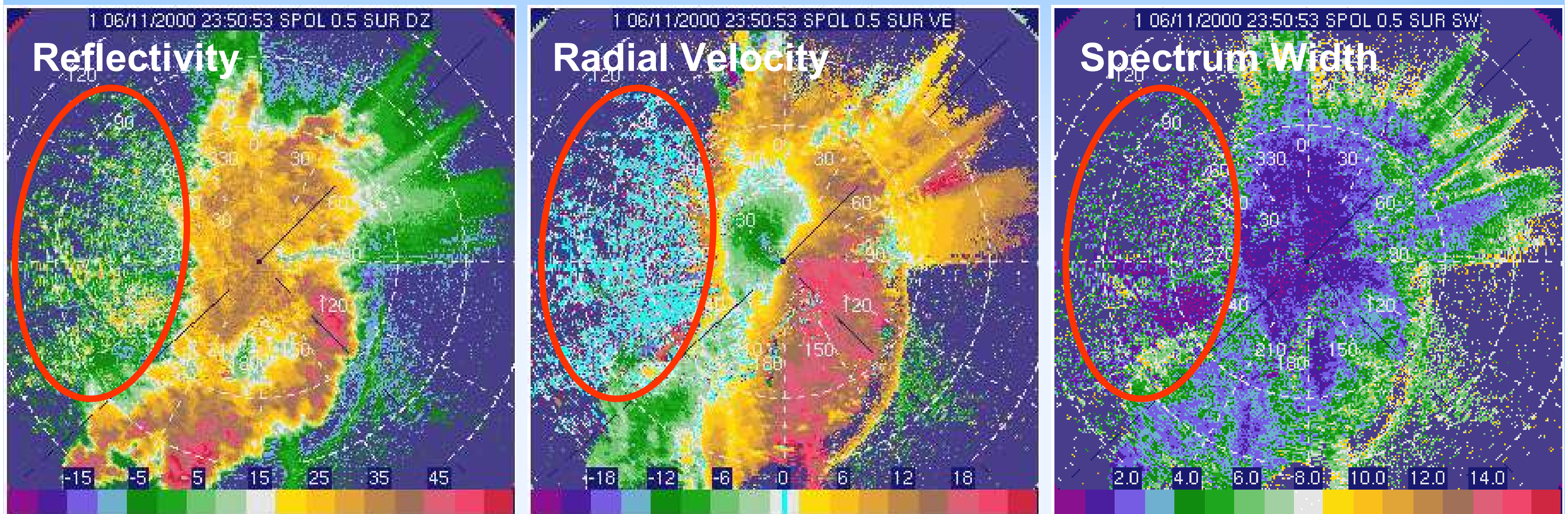
Schematic of REC



AP Detection Algorithm



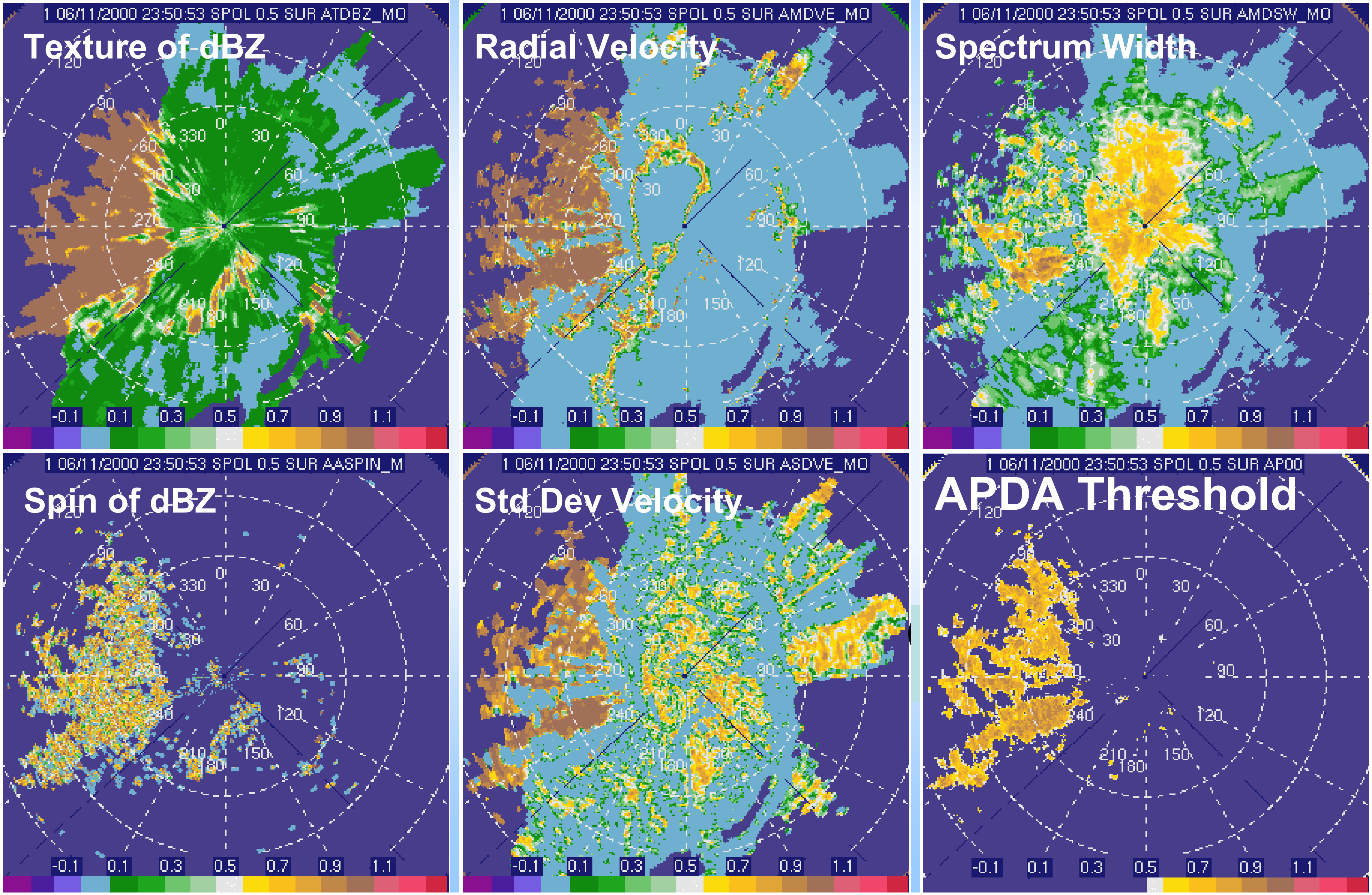
Radar Moment Fields



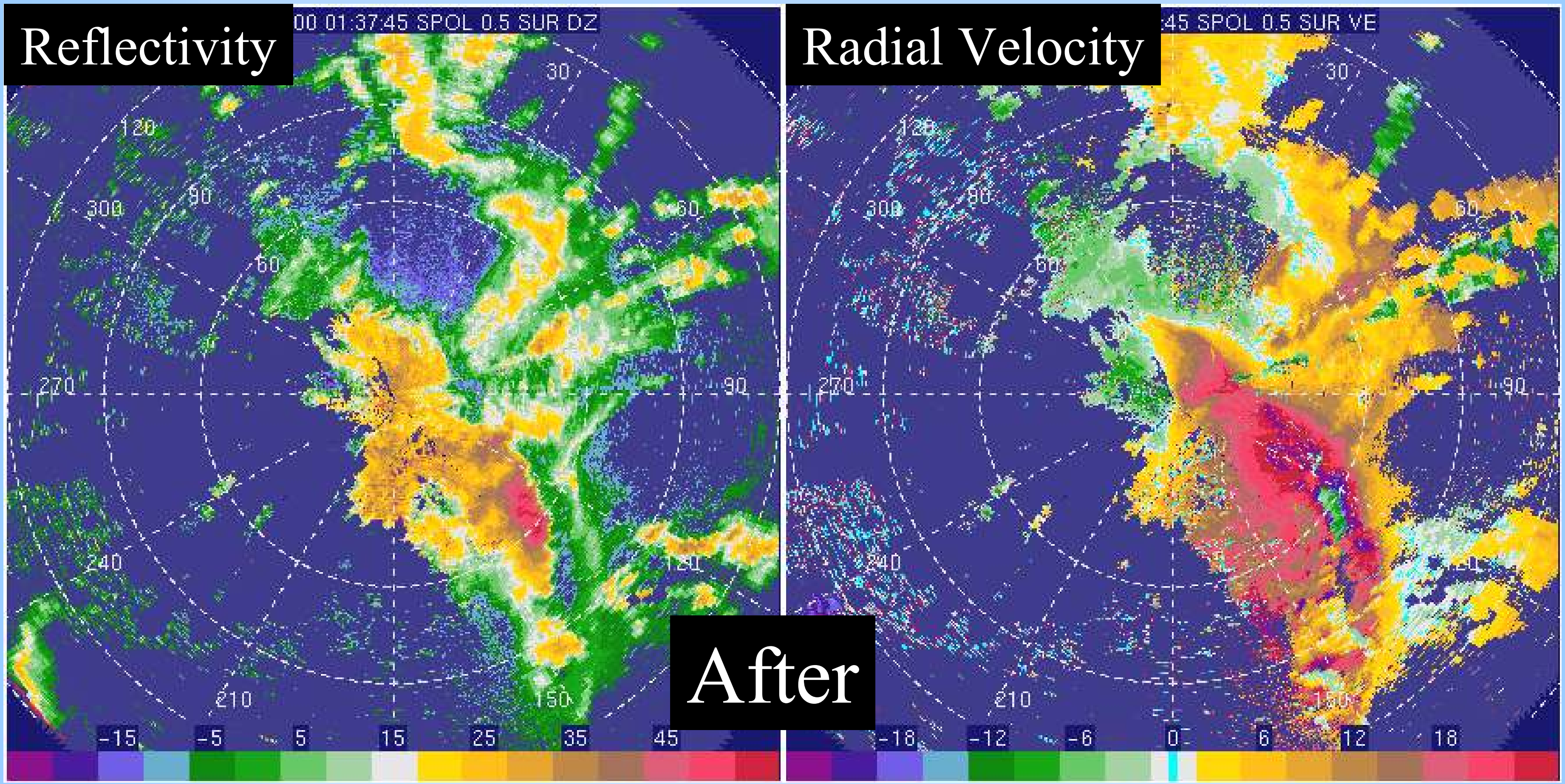
AP ground clutter

Moment fields are input into REC

APDA Final Output

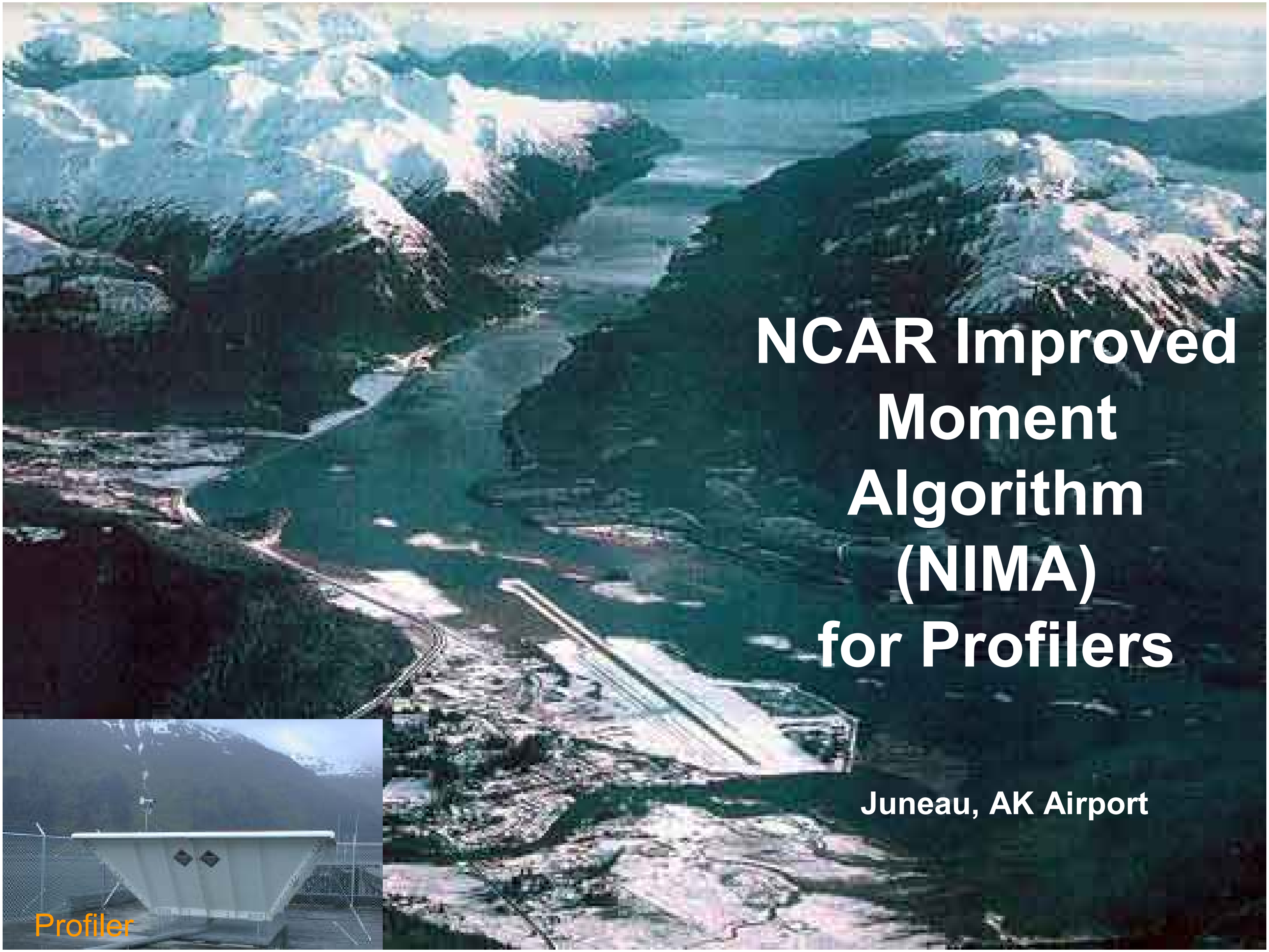


APDA as Threshold

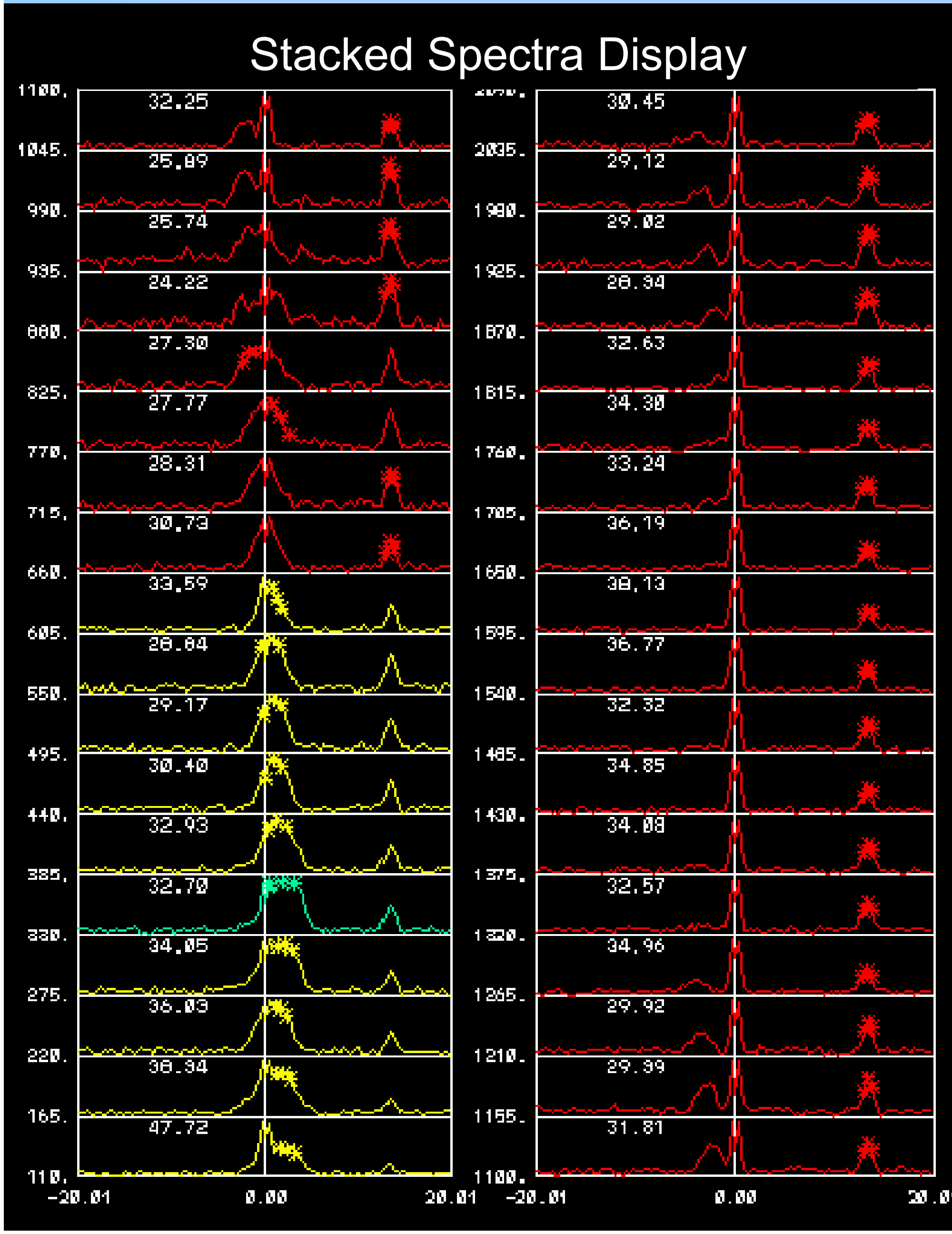


APDA is operational on WSR-88D radars

NCAR Improved Moment Algorithm (NIMA) for Profilers

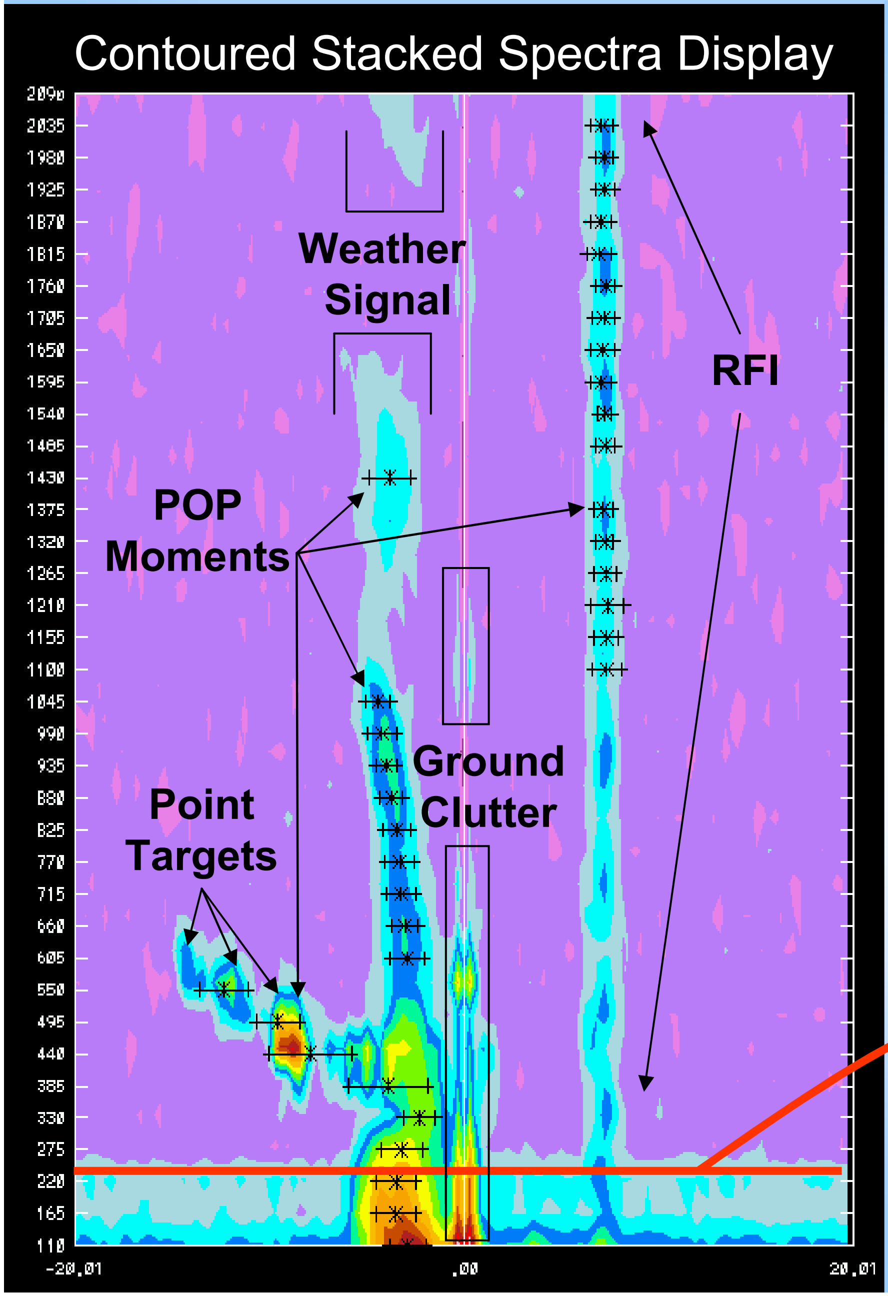


Profilers

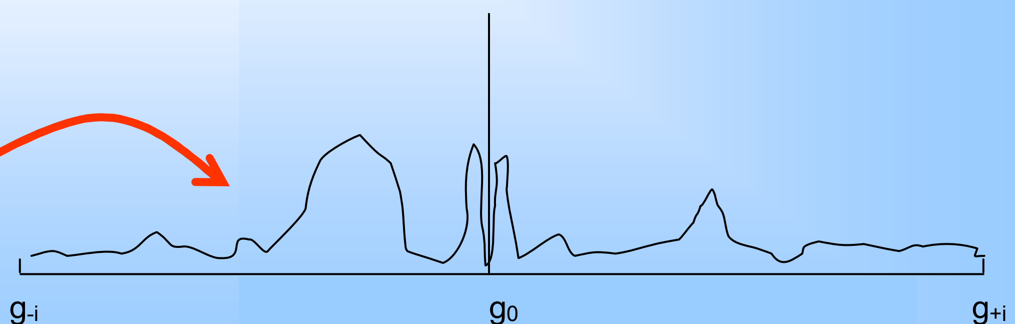


- Traditional signal processing computes the moments by selecting the peak spectral component
  - Profiler Online Program, or POP
- Spectral contamination can lead to errors
- NIMA developed for use at airports in high clutter environments
  - Operational at the Juneau, AK airport and the Hong Kong Chep Lap Kok airport

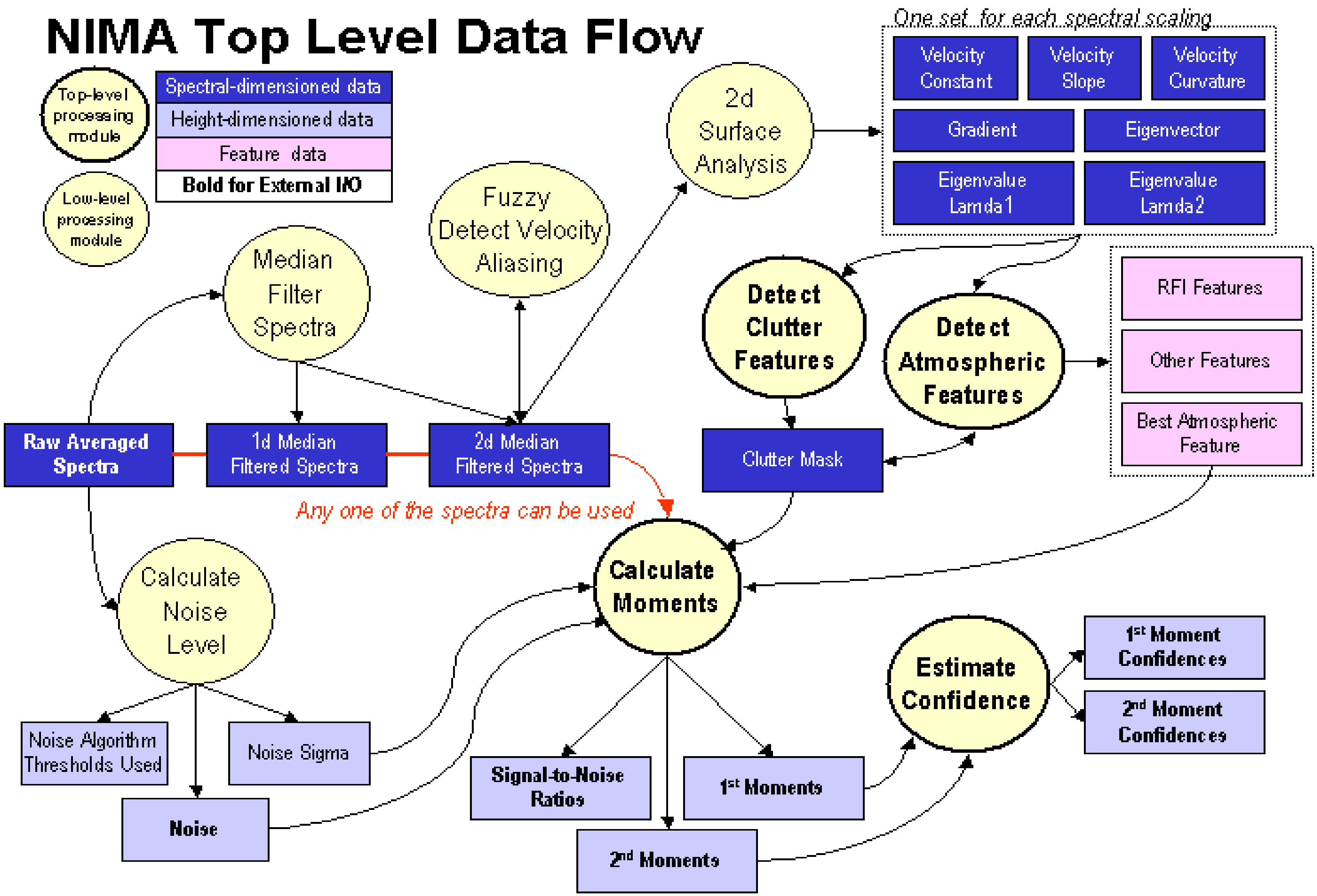
Meteorological Issues



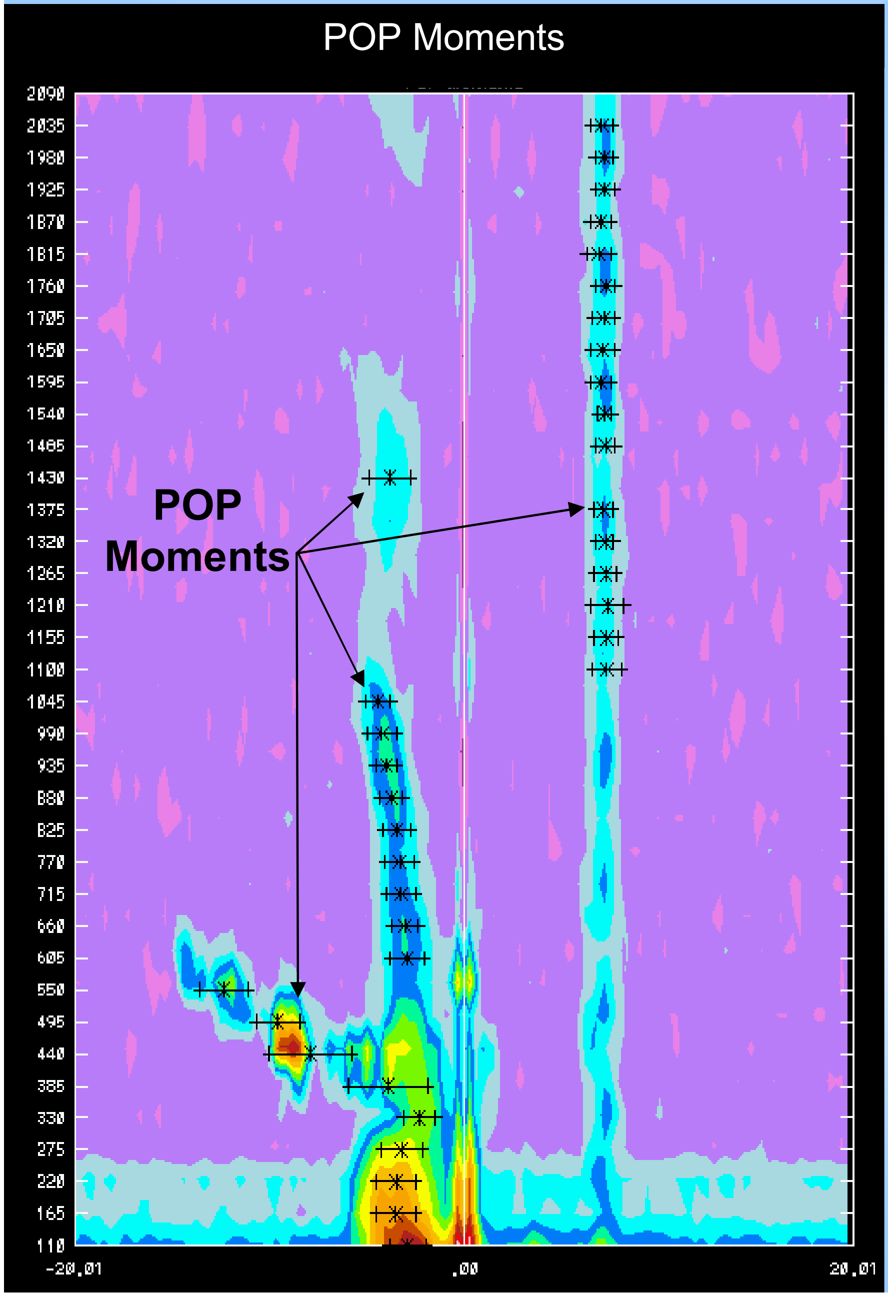
- Wind profiling radars produce Doppler velocity data often contaminated by
  - Ground clutter
  - Radio Frequency Interference (RFI)
  - Point Targets (aircraft and birds)
  - Noise
- Bad moments give bad winds and potential false alarms of wind shear

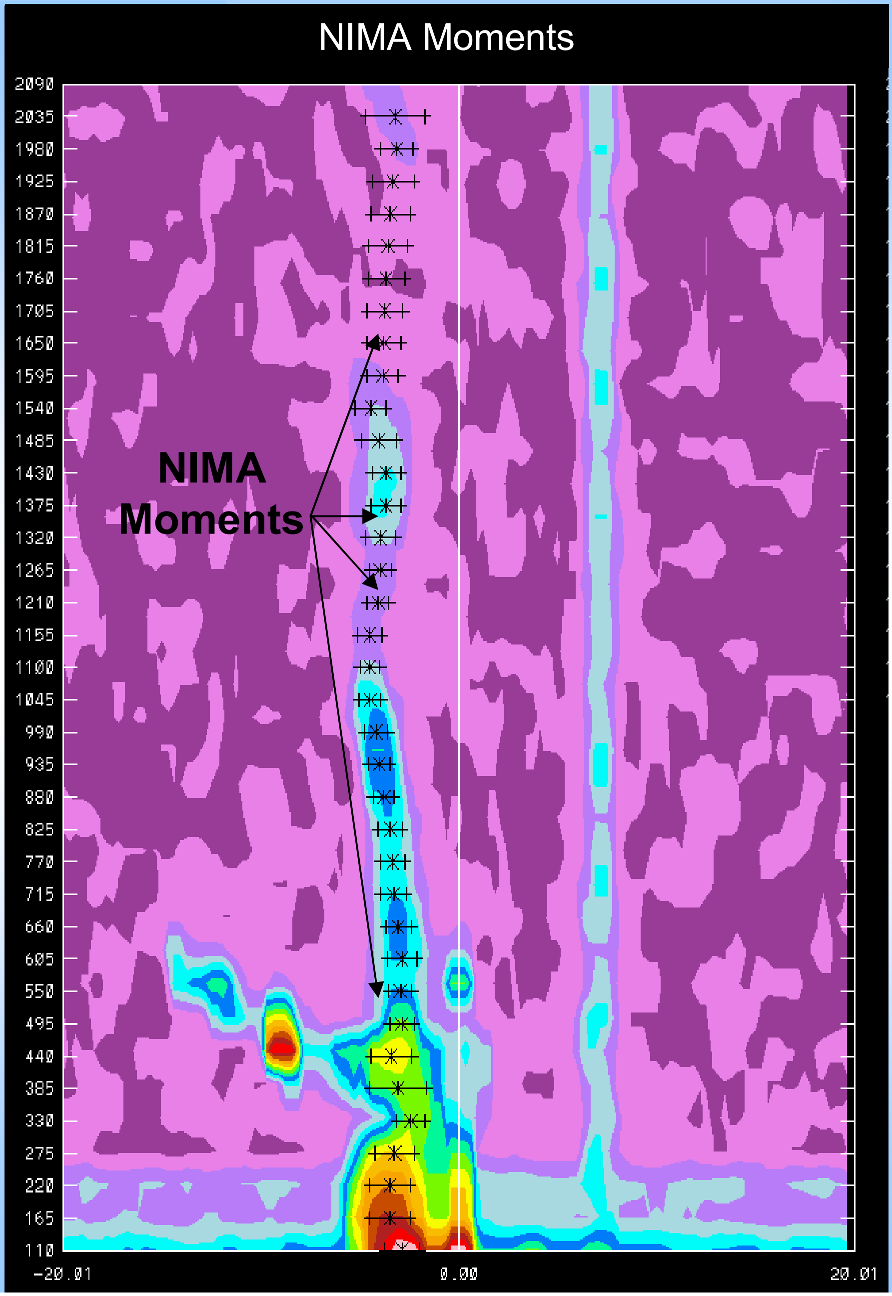


NIMA Top Level Data Flow



NIMA Results





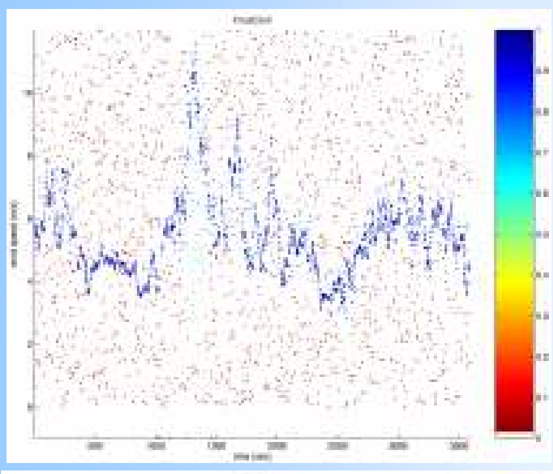
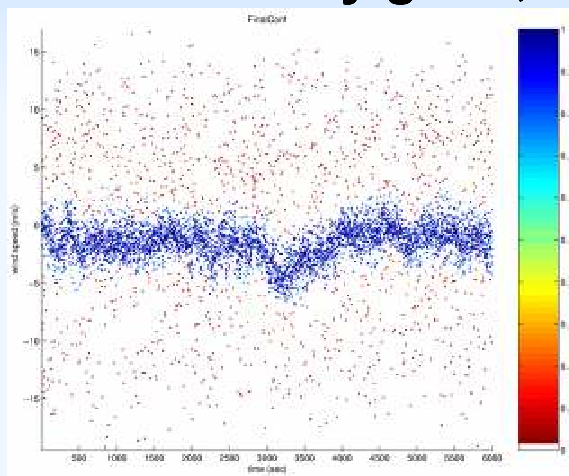
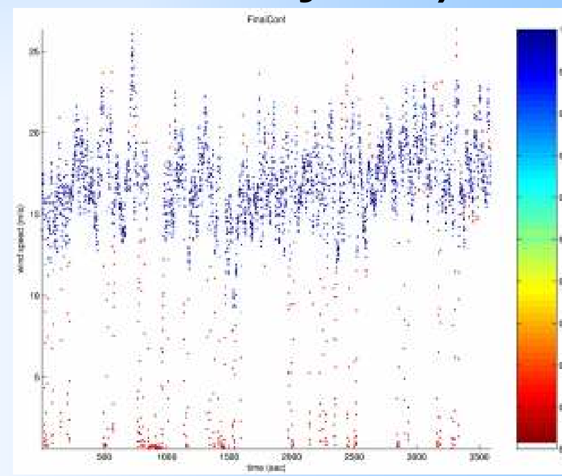
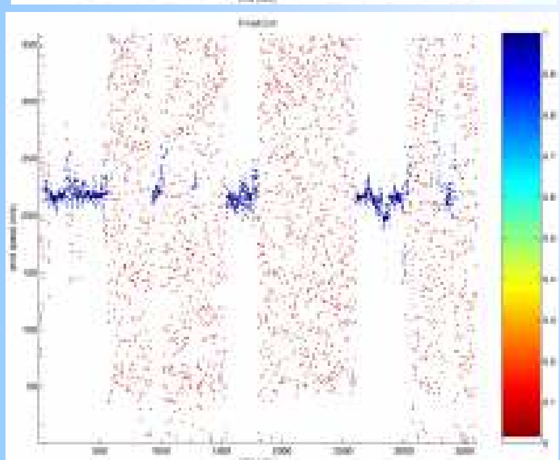
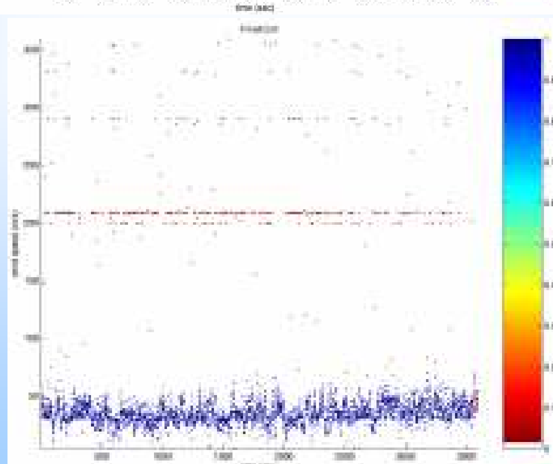
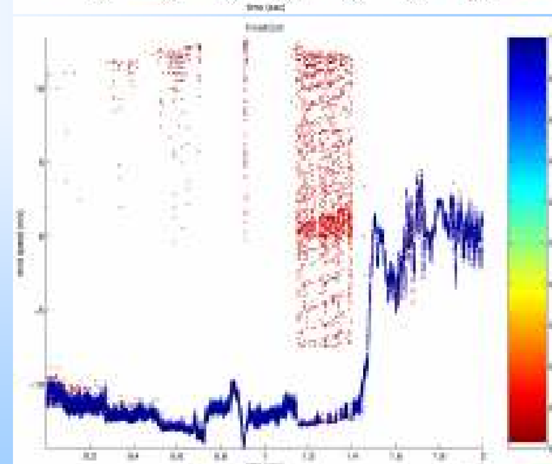
Intelligent Outlier Detection Algorithm (IODA) for Time-series Data

Photo: Dan Phillips

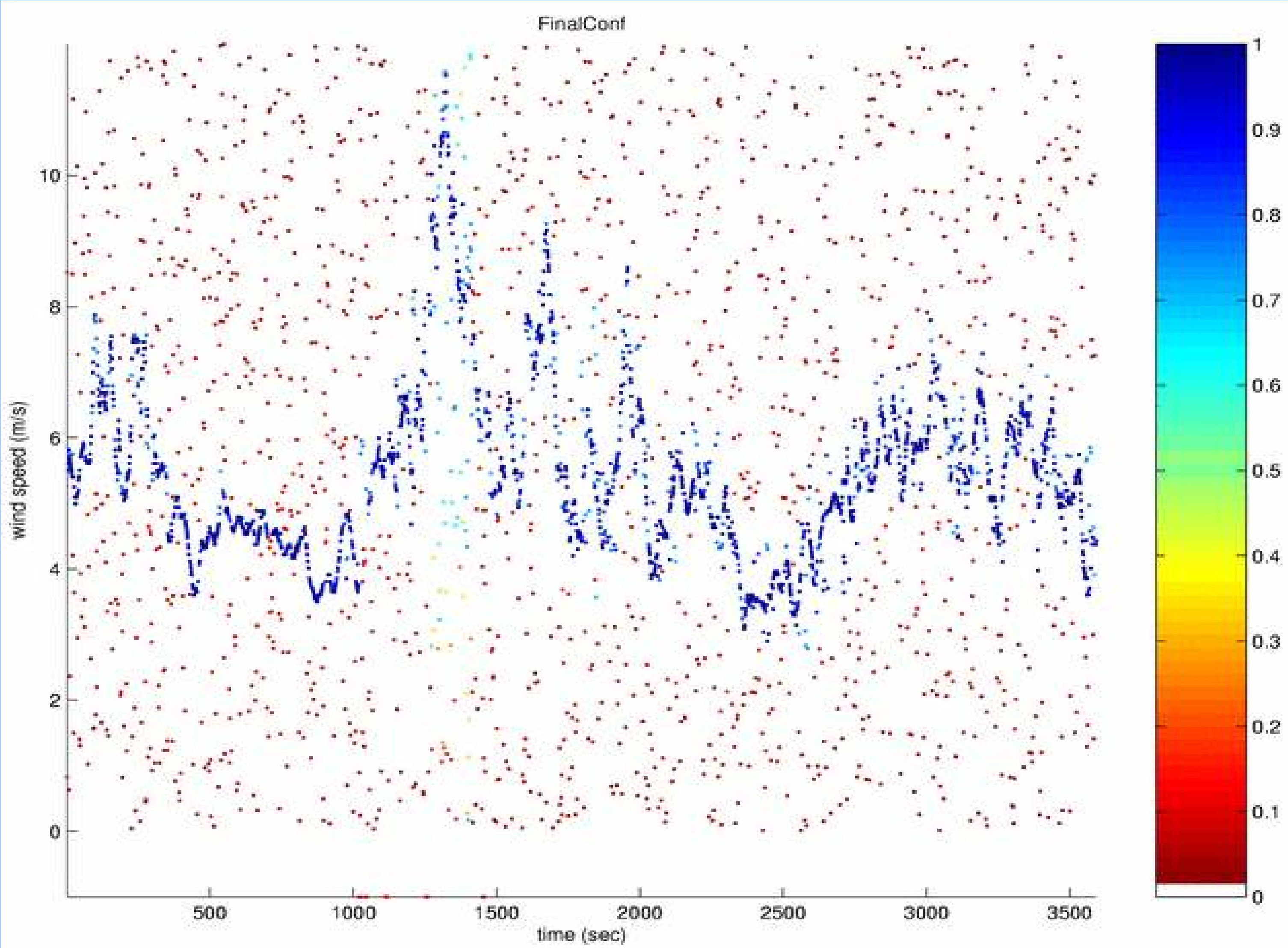
IODA Introduction

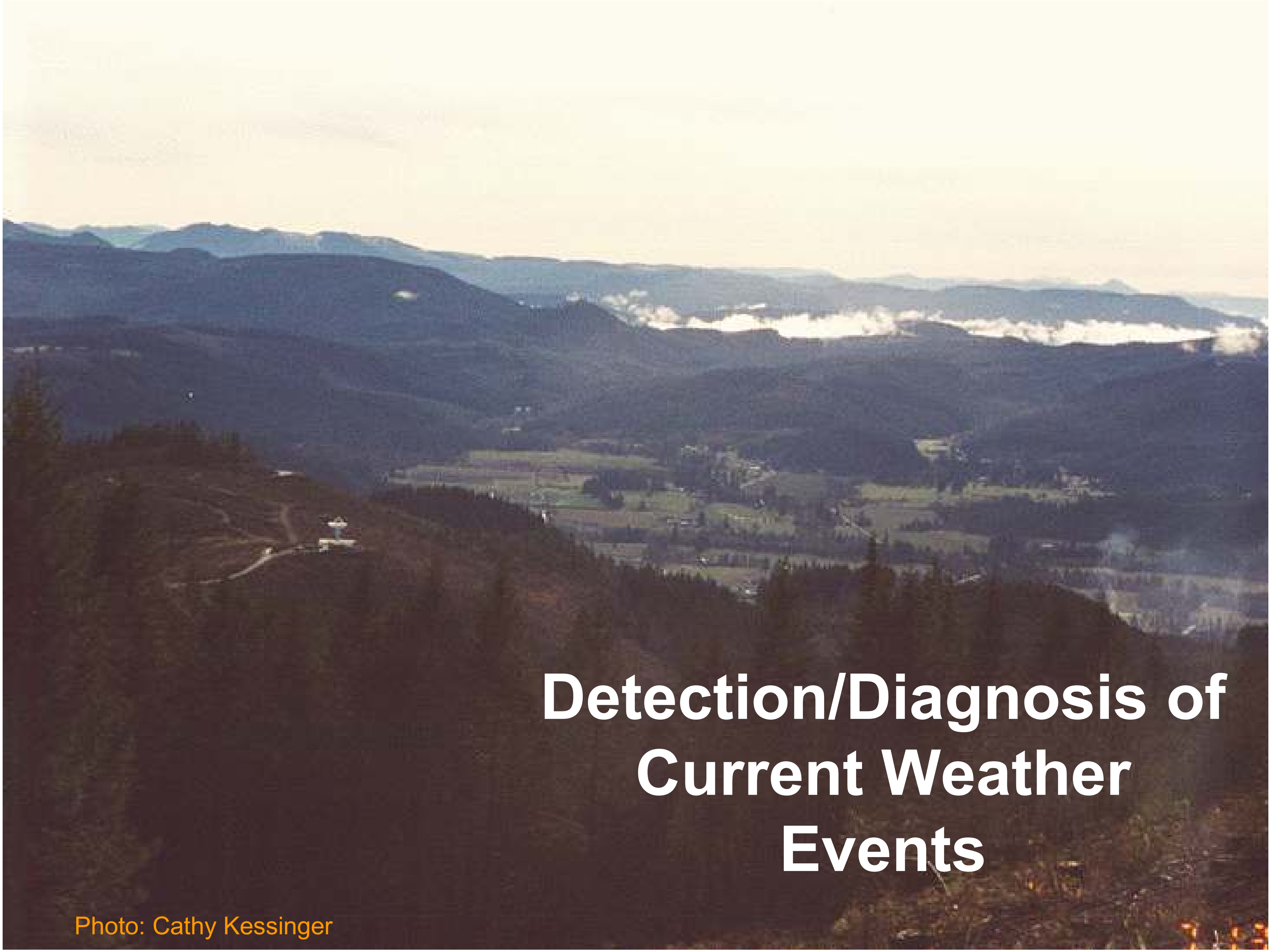
Example data signatures of sensor failure modes

After application of IODA, the data are assigned a quality assurance value (dark blue = very good, dark red = very bad)

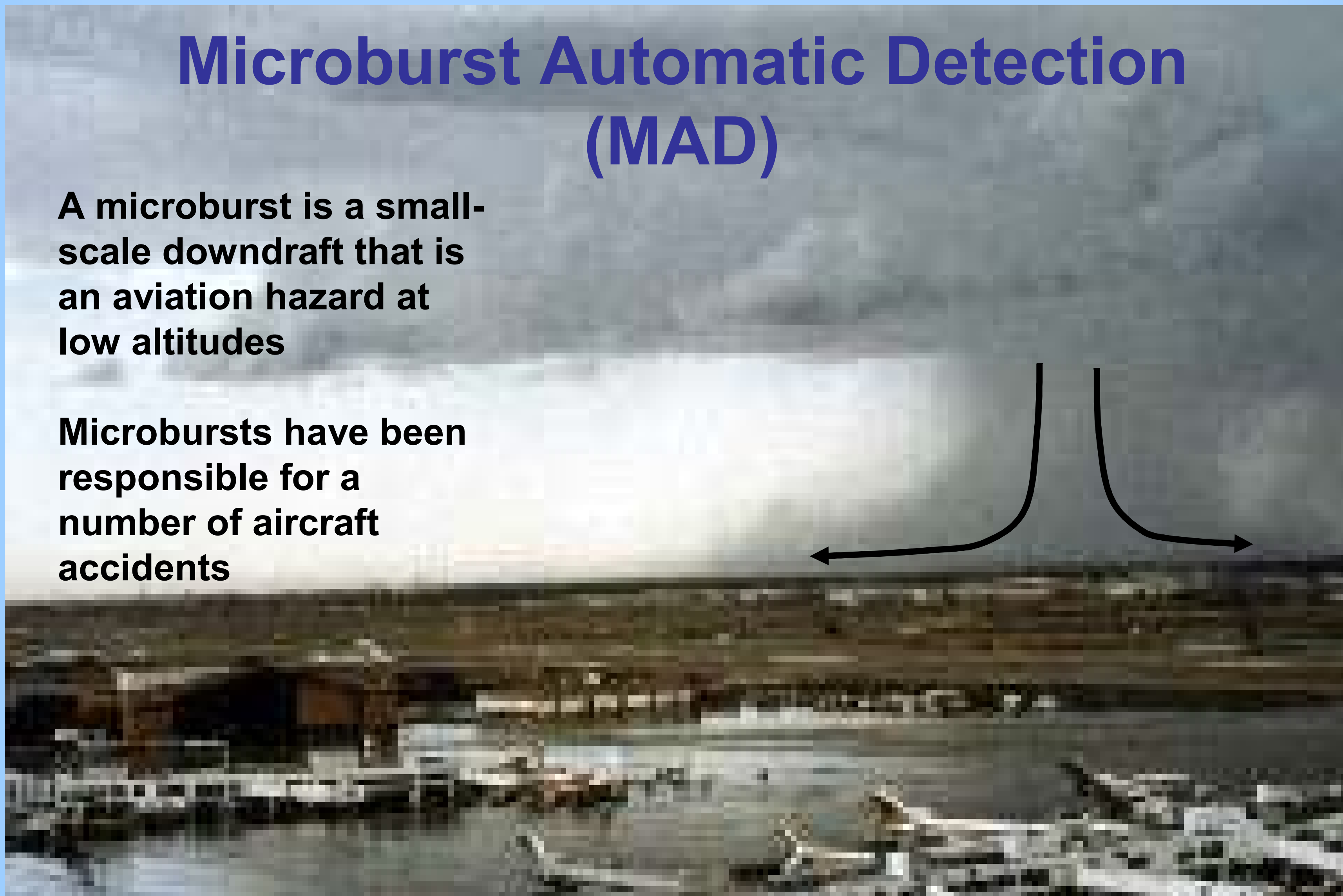







IODA Results




Detection/Diagnosis of
Current Weather
Events
Photo: Cathy Kessinger

Microburst Automatic Detection (MAD)



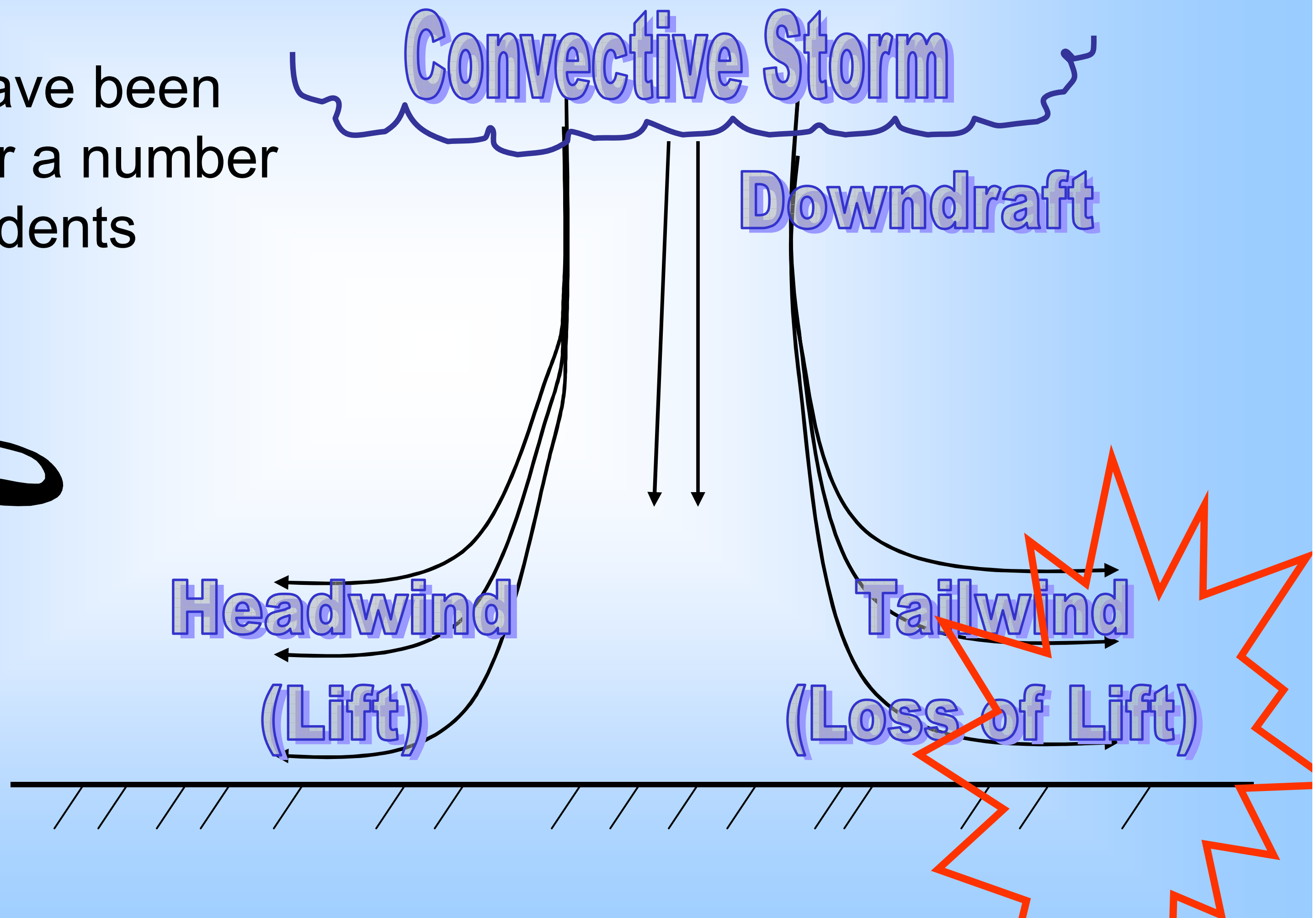
A microburst is a small-scale downdraft that is an aviation hazard at low altitudes

Microbursts have been responsible for a number of aircraft accidents

Meteorological Problem

- A microburst is a small-scale downdraft that is an aviation hazard at low altitudes.

Microbursts have been responsible for a number of aircraft accidents



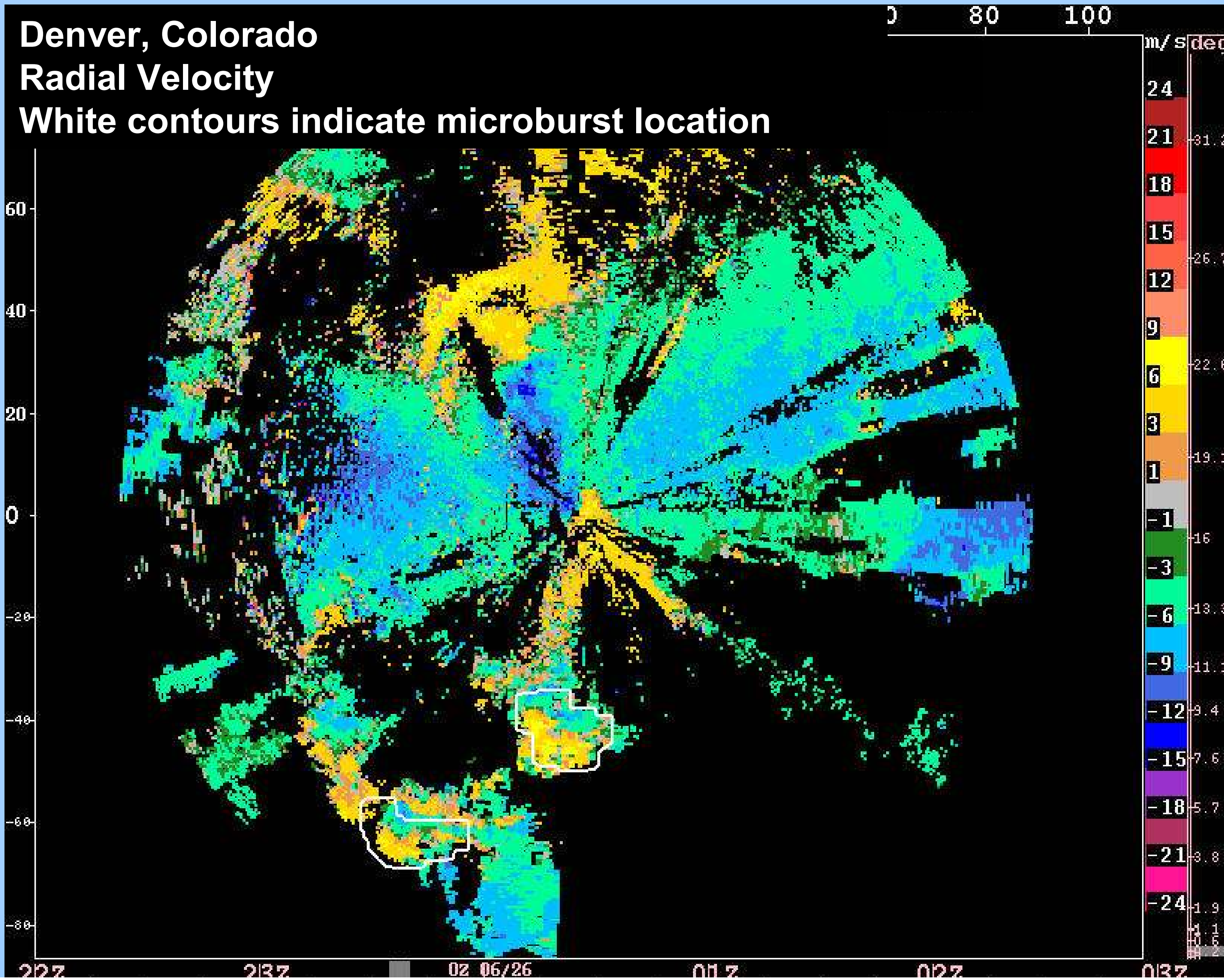
Meteorological Problem

- Microburst Characteristics
  - Divergent outflow
  - Near a storm
  - Characteristic size and shape
    - Not too big, not too small
    - Individual microbursts are roughly circular
    - Can have a line microbursts
  - Characteristic lifetime (minutes)

MAD Algorithm

- Algorithm Characteristics
  - Divergent shear is the principle indicator of a microburst
  - Being near a storm enhances interest
  - Being near an earlier microburst location enhances interest
  - Areas of high interest that “look like a microburst” determine current detection

TDWR Case Study from 25 June 2001



Current Icing Potential (CIP)


Rime icing under aircraft wing


Clear glaze on aircraft wing


Icing on Rosemount reverse flow

The Meteorological Problem

- Identify where inflight icing (supercooled liquid water, SLW) is likely to exist
- Assign attributes such as icing severity and type

SLW associated with:

• clouds

• precipitation

• in-flight temperature range (~0 to –20^{o}C or so)

• upward vertical velocity

• There are many causes and precursors!

CIP Algorithm Philosophy

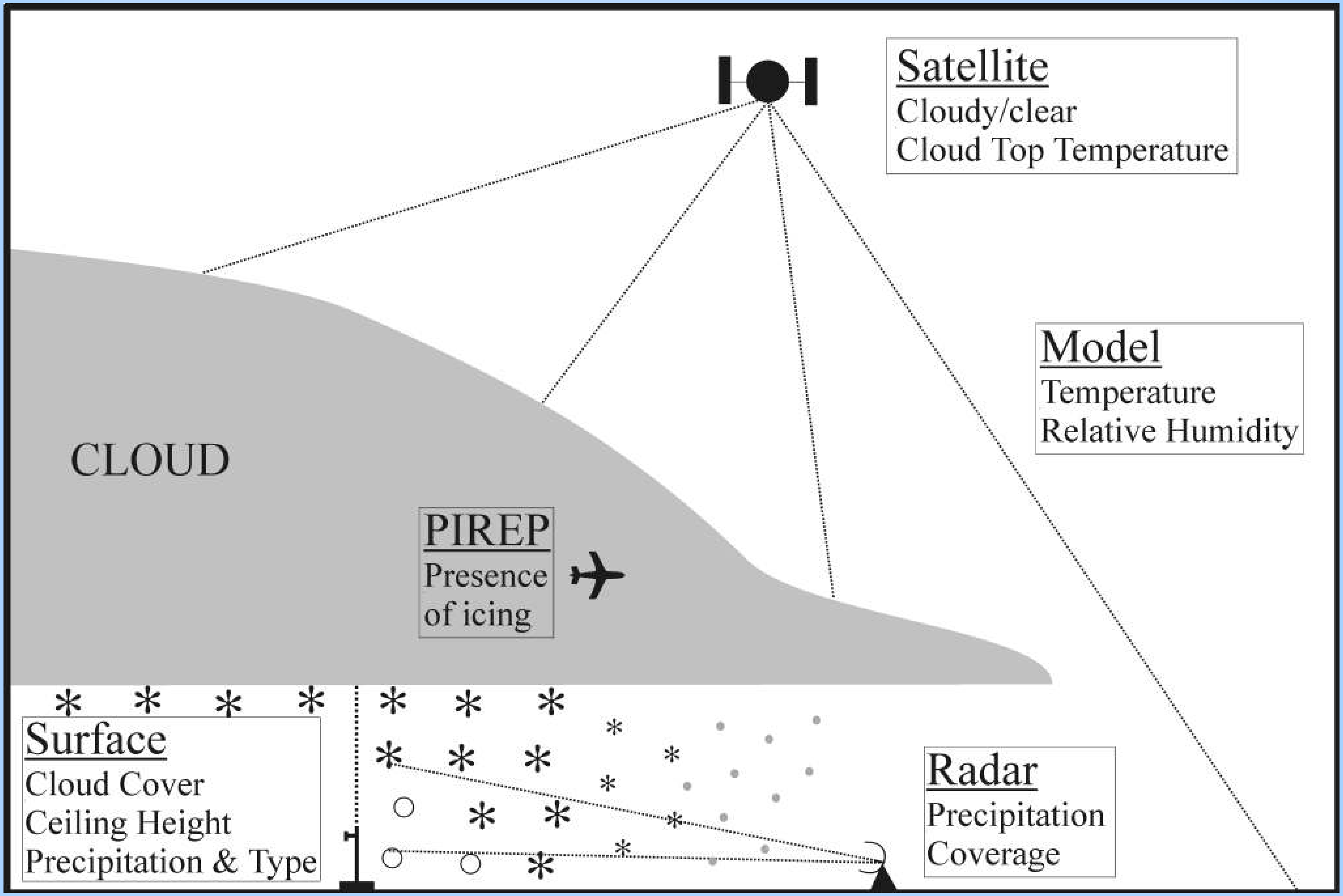
Different sources of information provide clues as to where icing <u>IS</u> and <u>IS NOT</u> present

Weather scenarios govern details of mapping functions

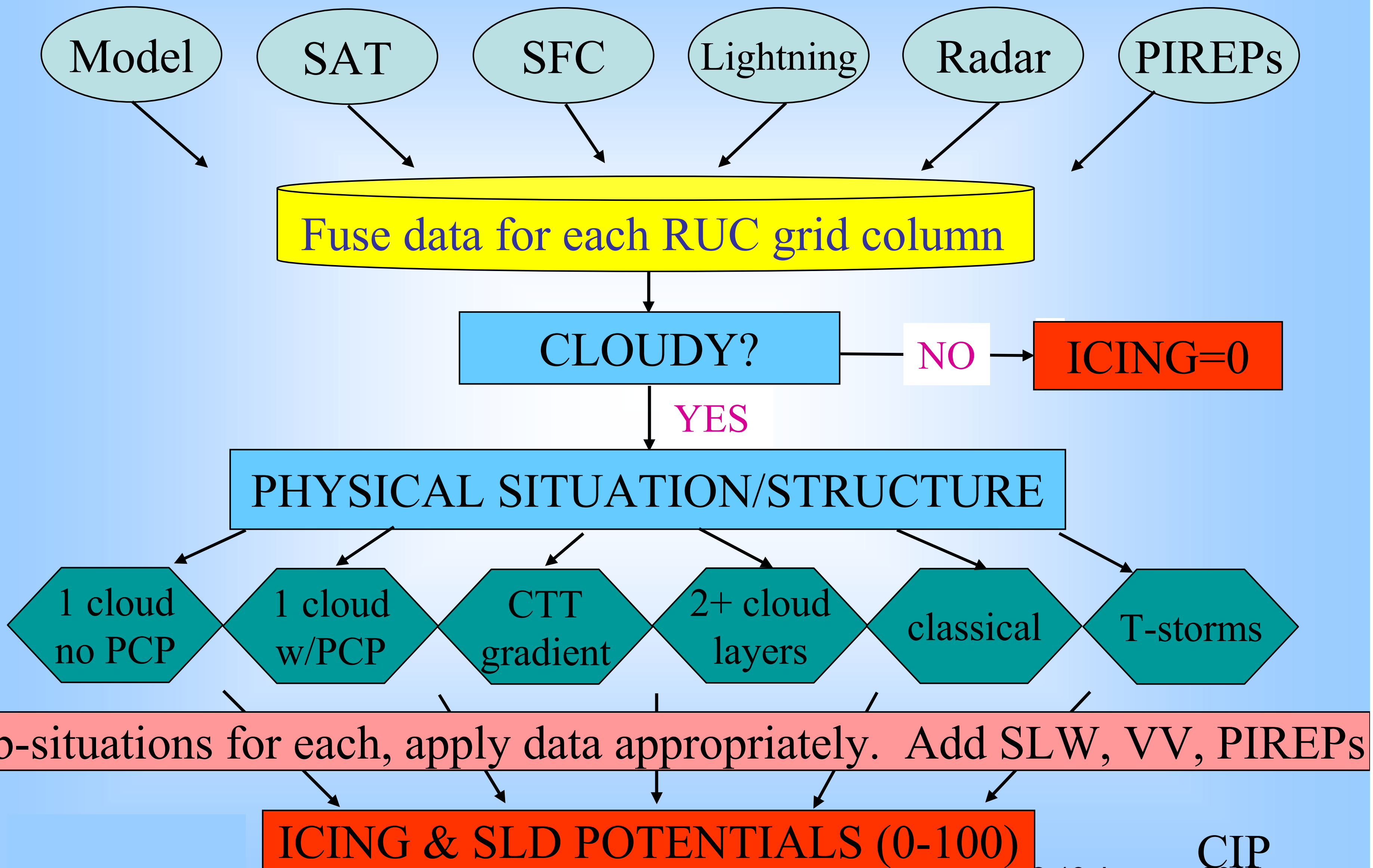
Create a system that mimics manual forecast techniques
Map “interest” in certain icing-related weather parameters

Apply fields using a physically-based, situational approach

The CIP Algorithm

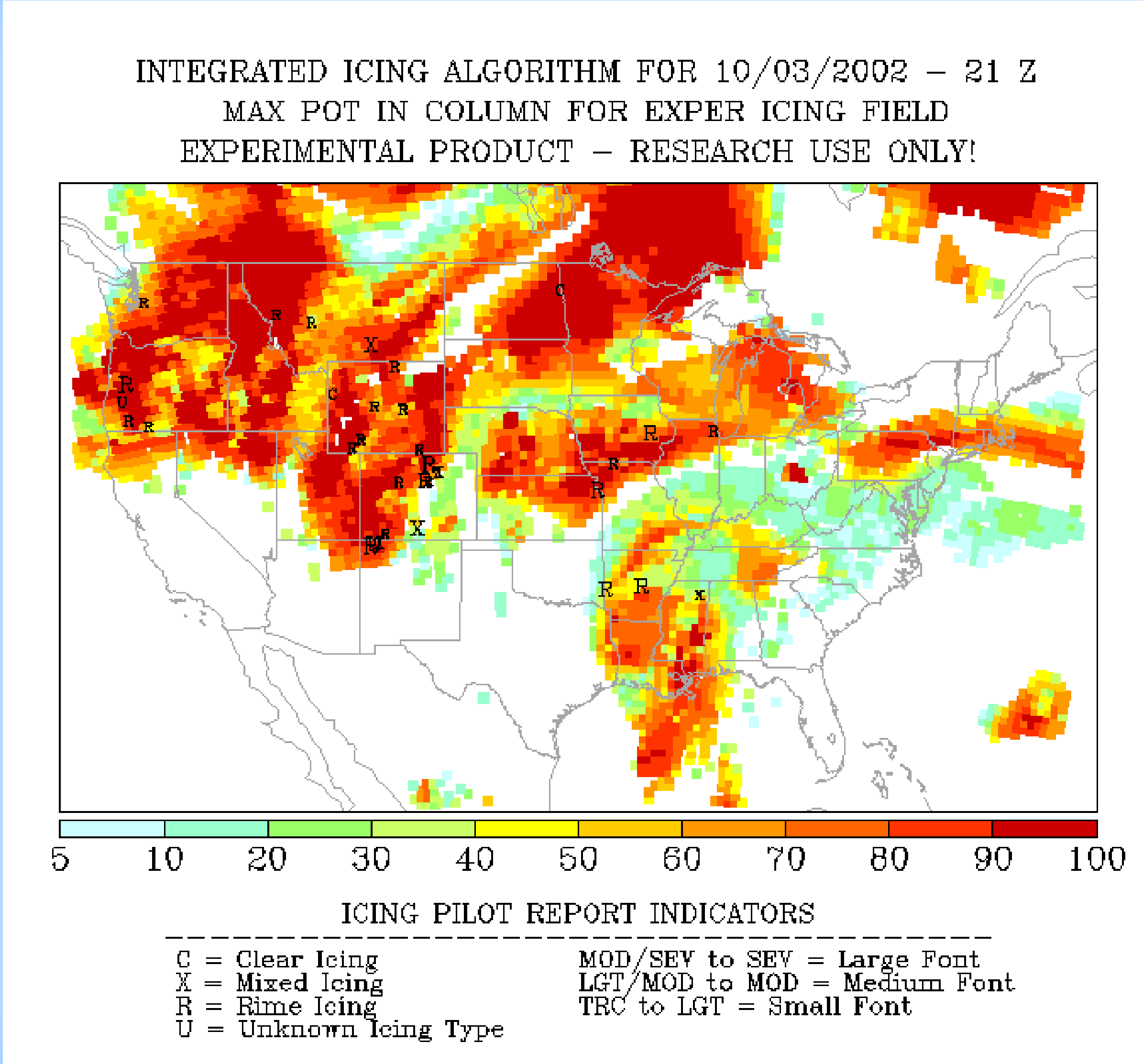


Integrate, apply by situation



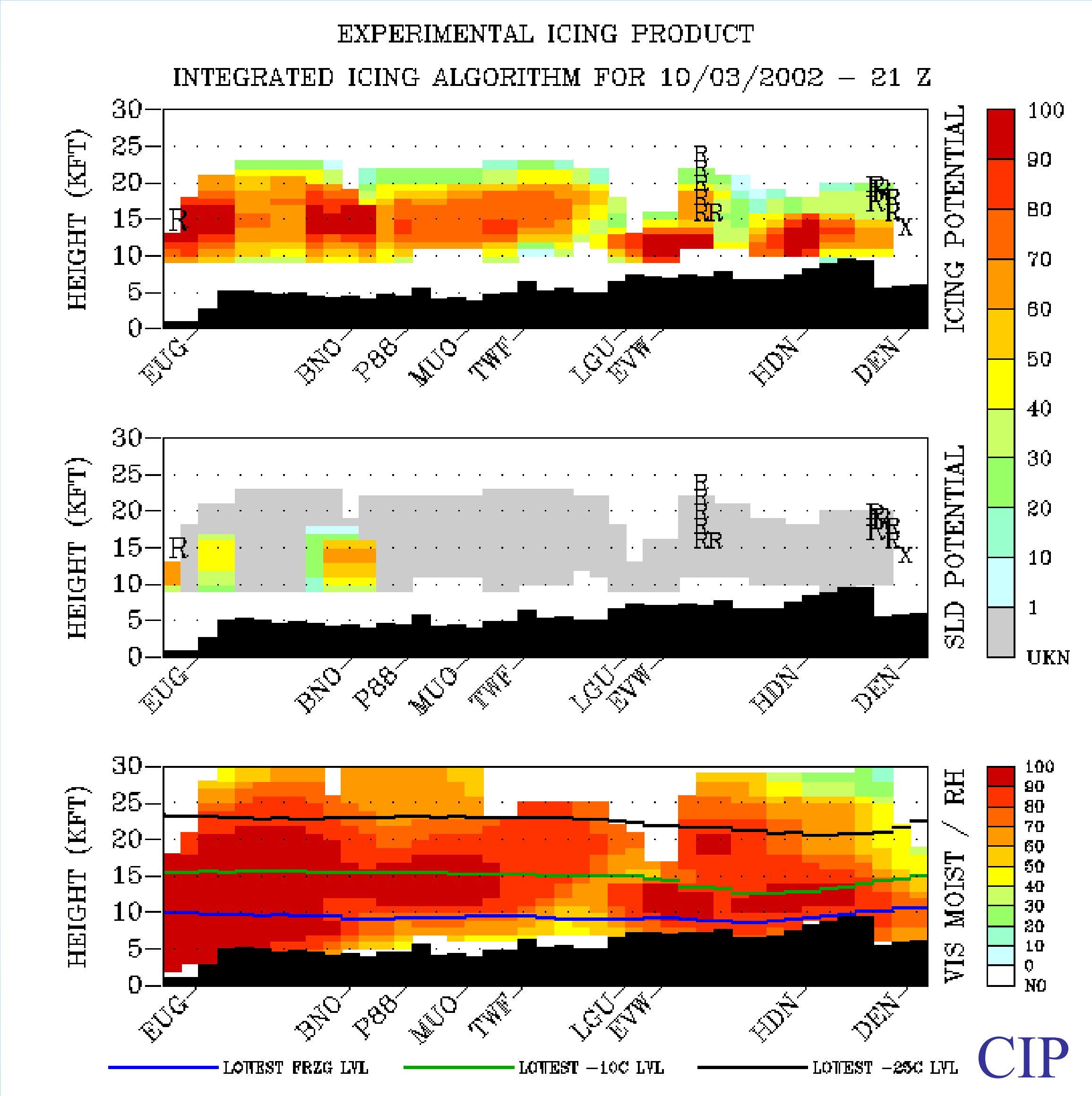
CIP

CIP – Maximum Icing Composite

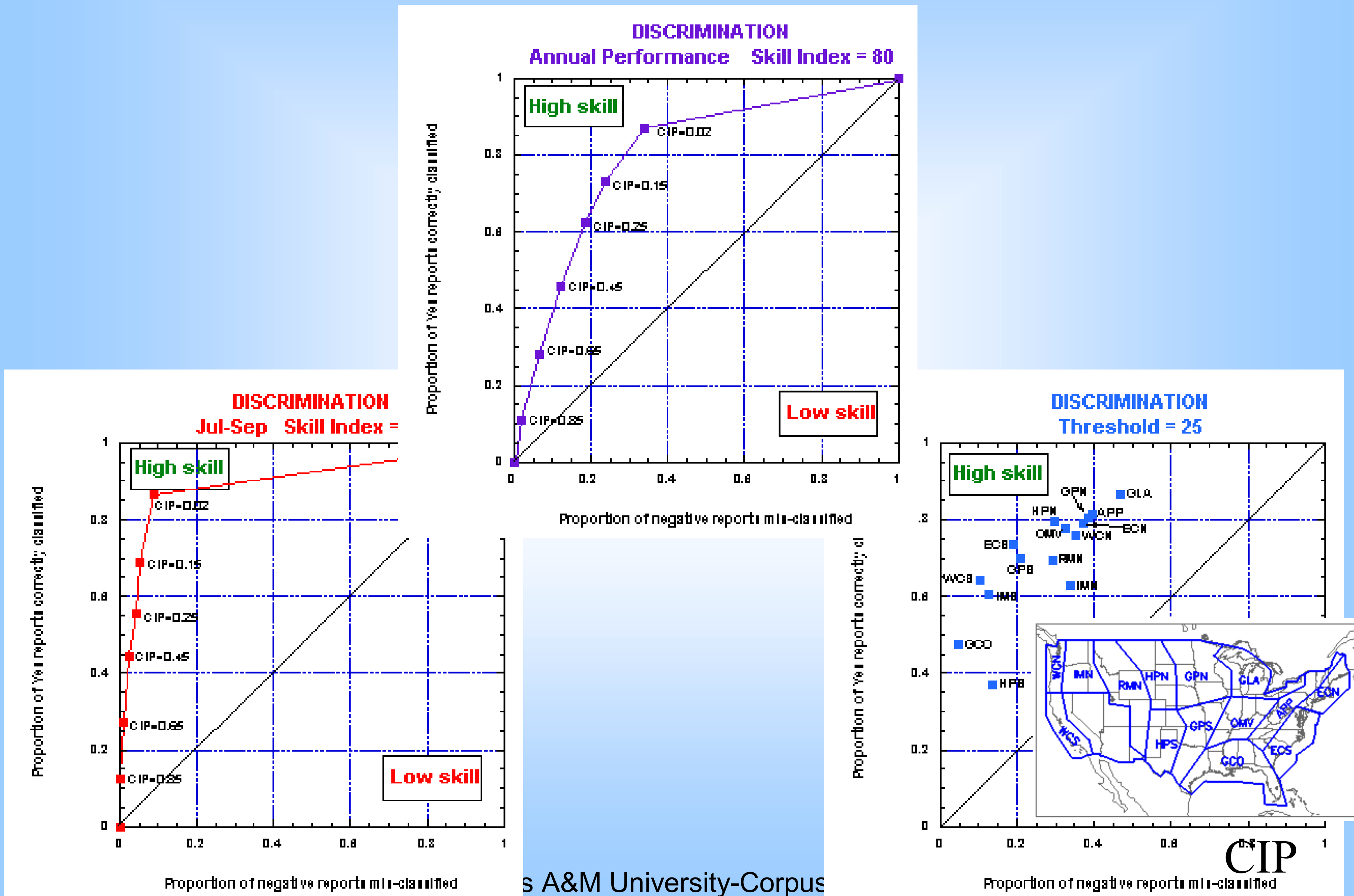


CIP

CIP – Vertical Slice



CIP Results: Verification



s A&M University-Corpus

Particle Classification Using S-Band Polarization Radar Measurements

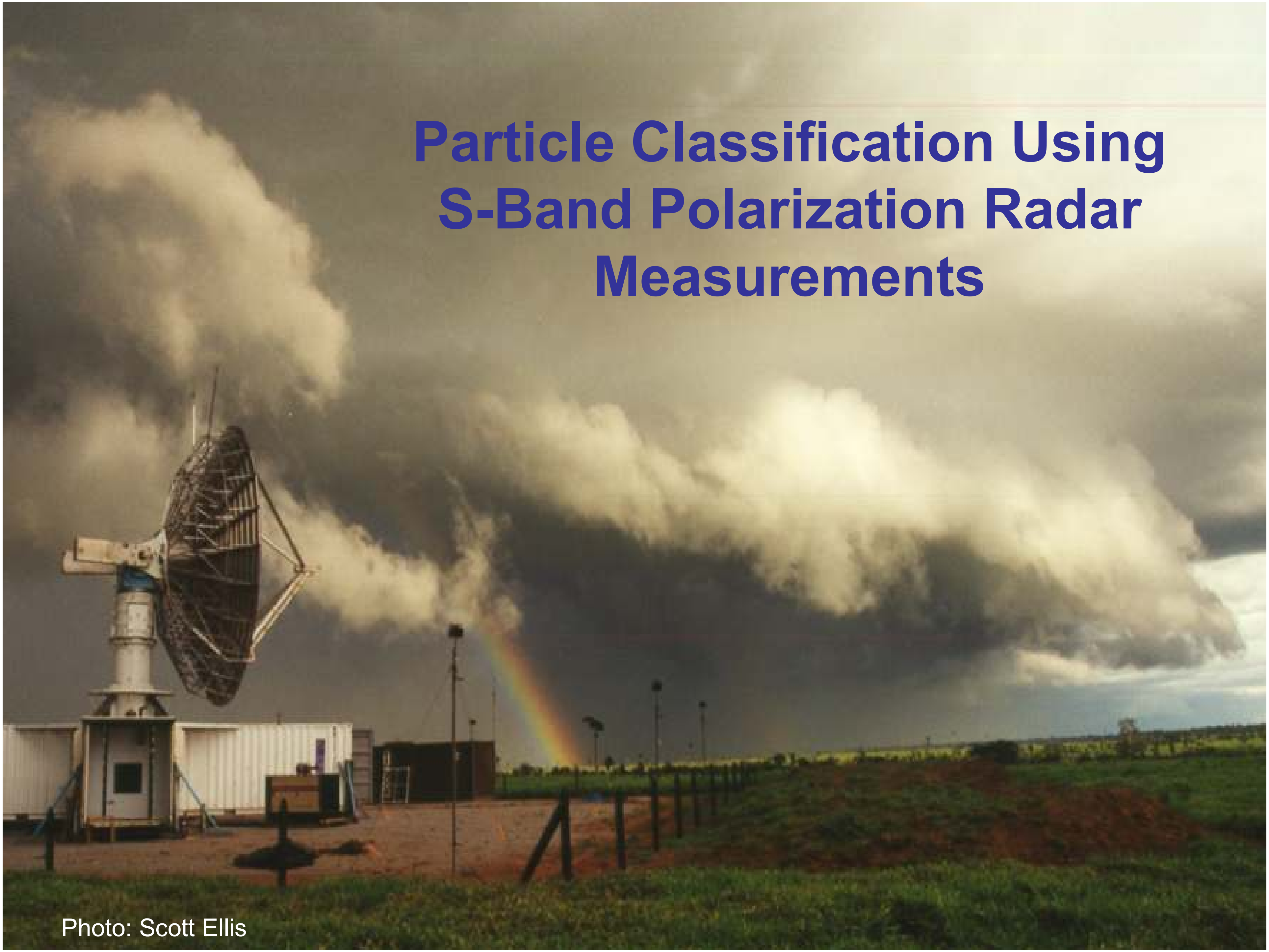
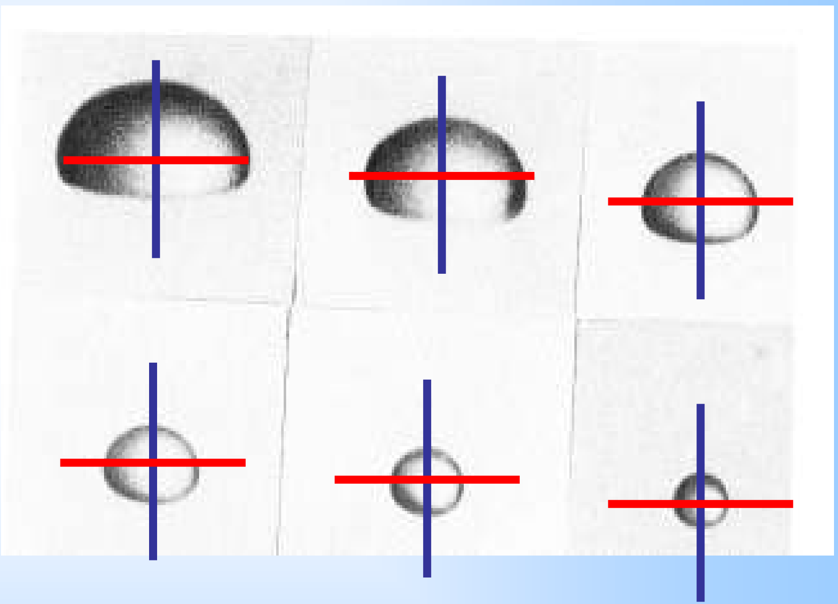


Photo: Scott Ellis

Polarimetric Measurements

- Polarimetric variables depend on particle axis ratio and refractive index.

A combination of measurements can be used to identify particles



From Pruppacher and Klett 1997

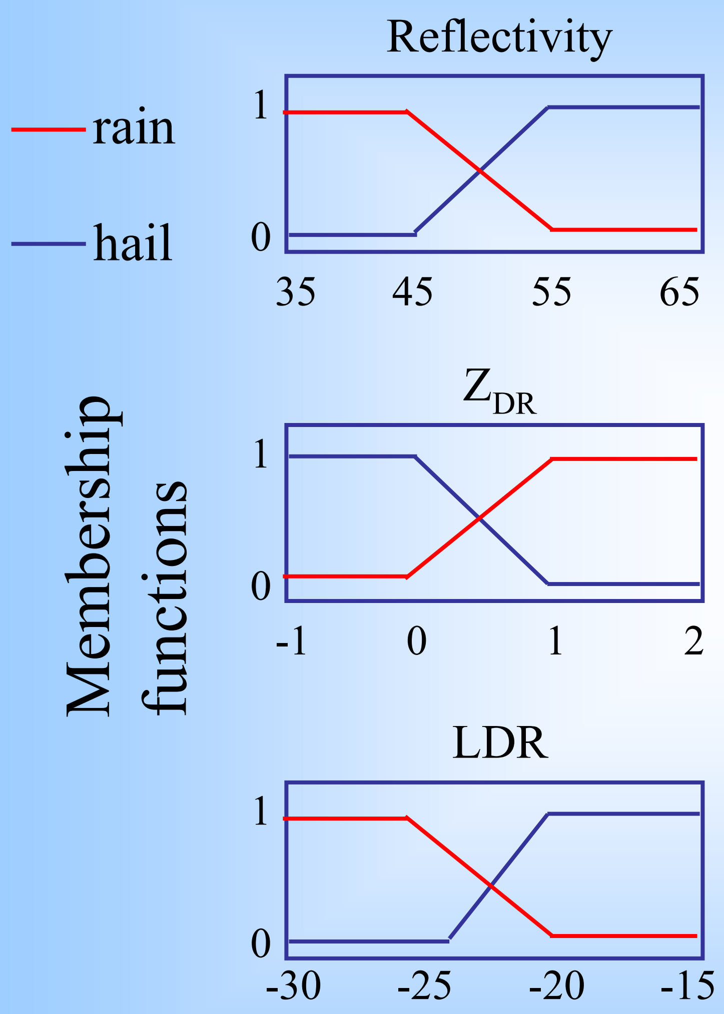
Applications for Particle Classification

- Radar data quality
  - Ground clutter
  - Second trip
- Detection hail
  - Improve rainfall estimates
  - Severe weather warning
- Cloud/precipitation physics
- Operational interpretation

Particle Classification Inputs

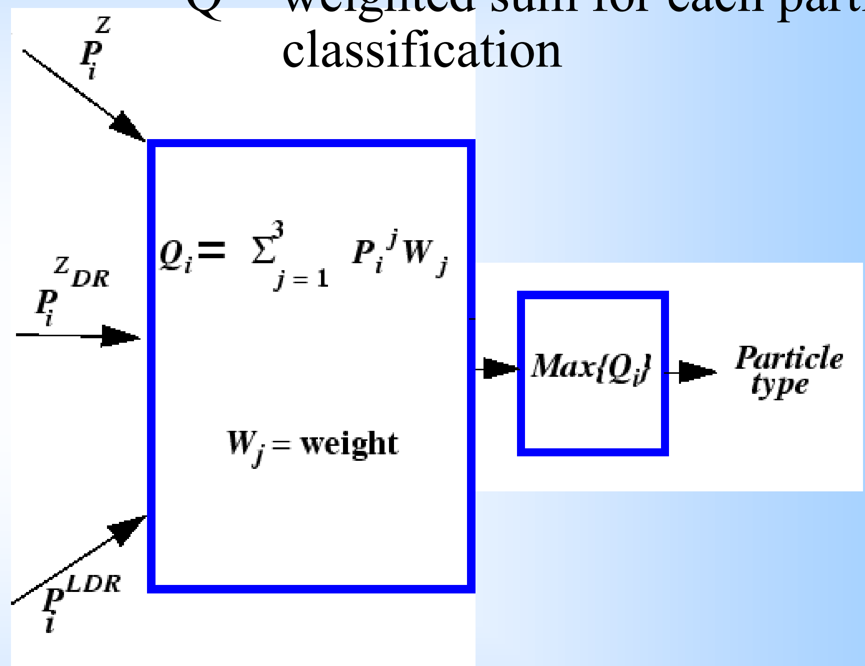
- Radar measurements used in algorithm
  - Z
  - Z_{DR}
  - K_{DP}
  - ρ_{HV}
  - LDR
- Temperature – from sounding/aircraft
- Derived quantities
  - $\sigma(\Phi_{DP})$
  - $\sigma(V)$
  - $\sigma(Z_{DR})$

Particle Classification



P = membership value

Q = weighted sum for each particle classification

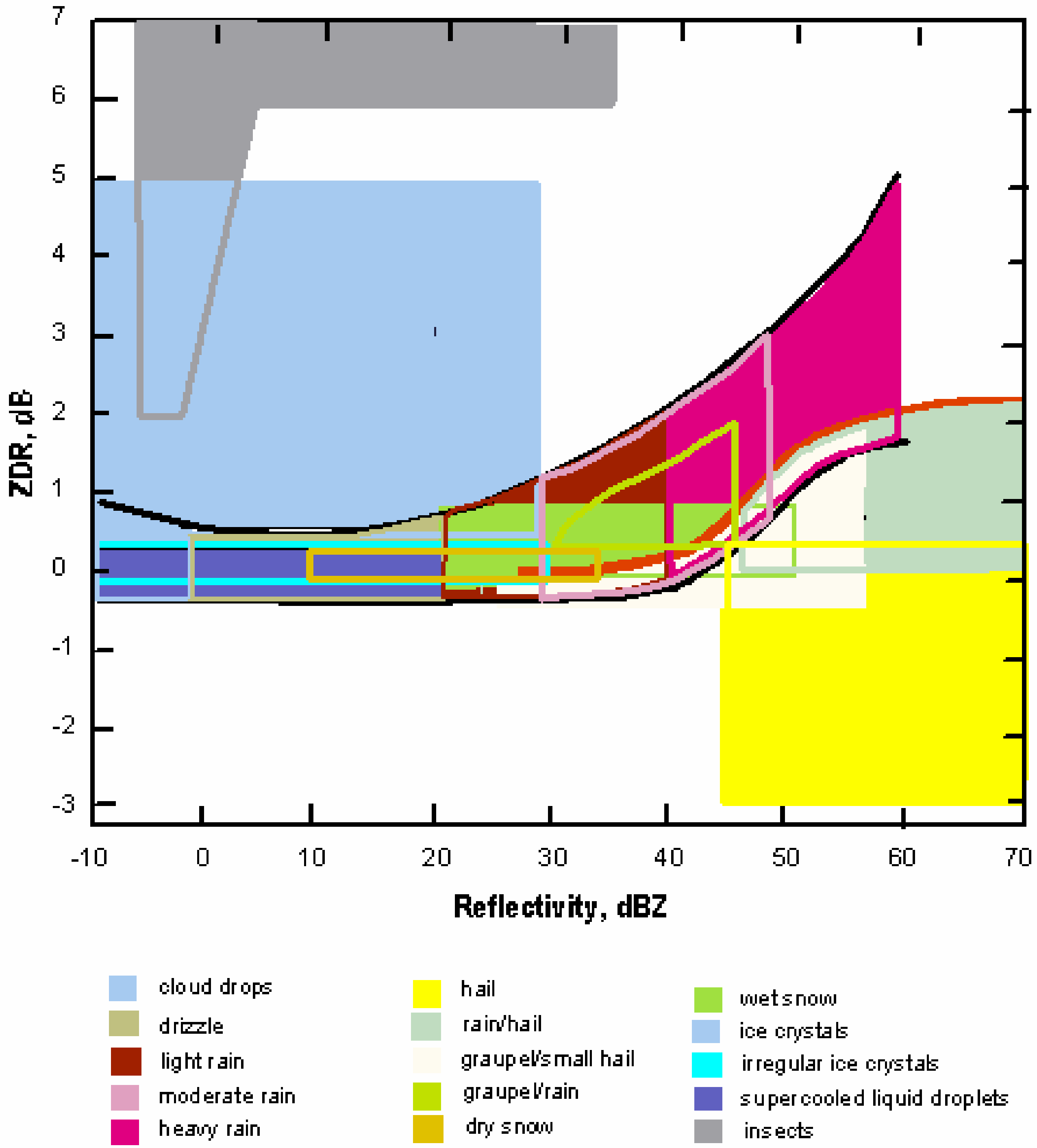


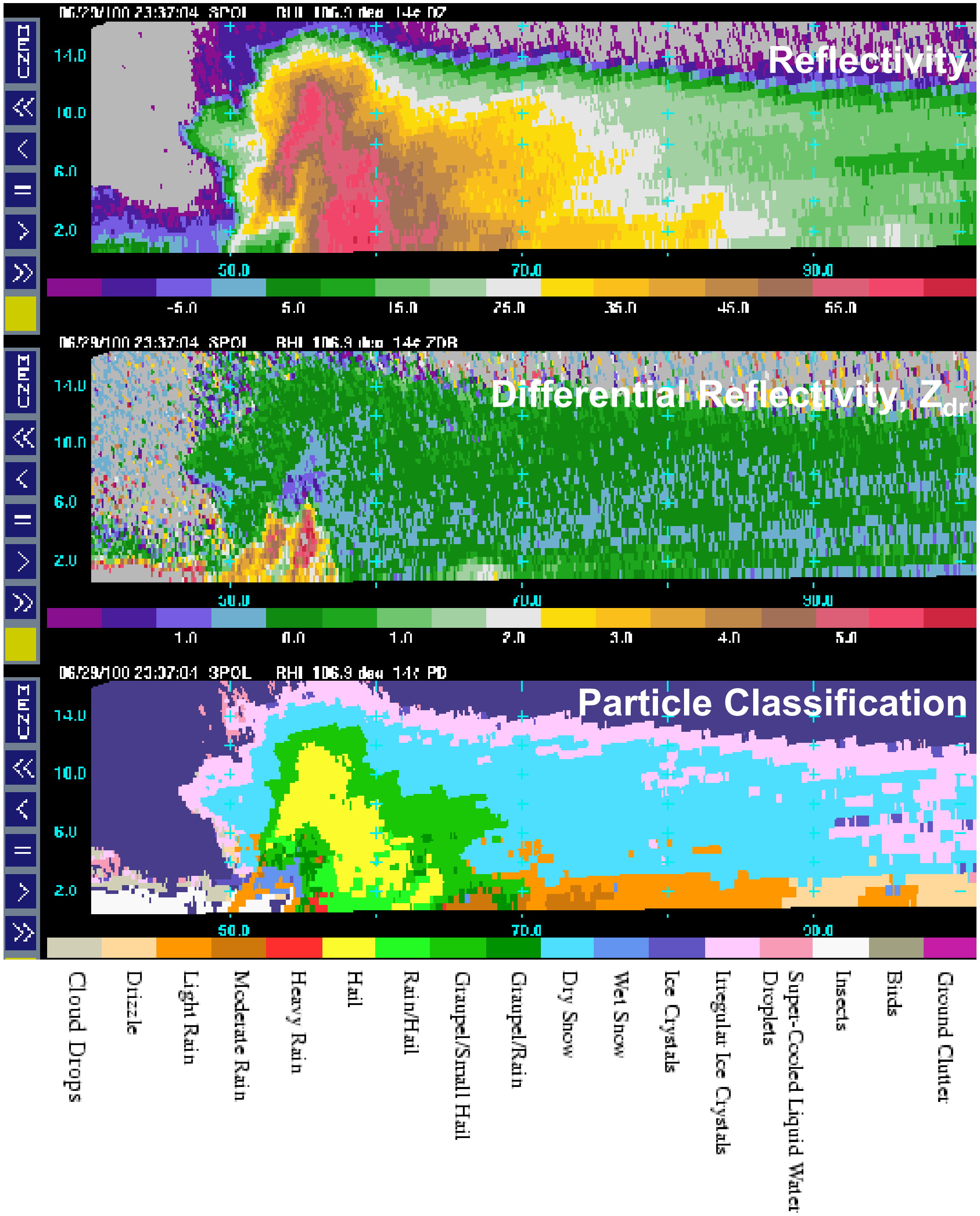
Example classifier for rain and hail

2-D Membership Functions

15 categories of particle type

Overlapping boundaries between types

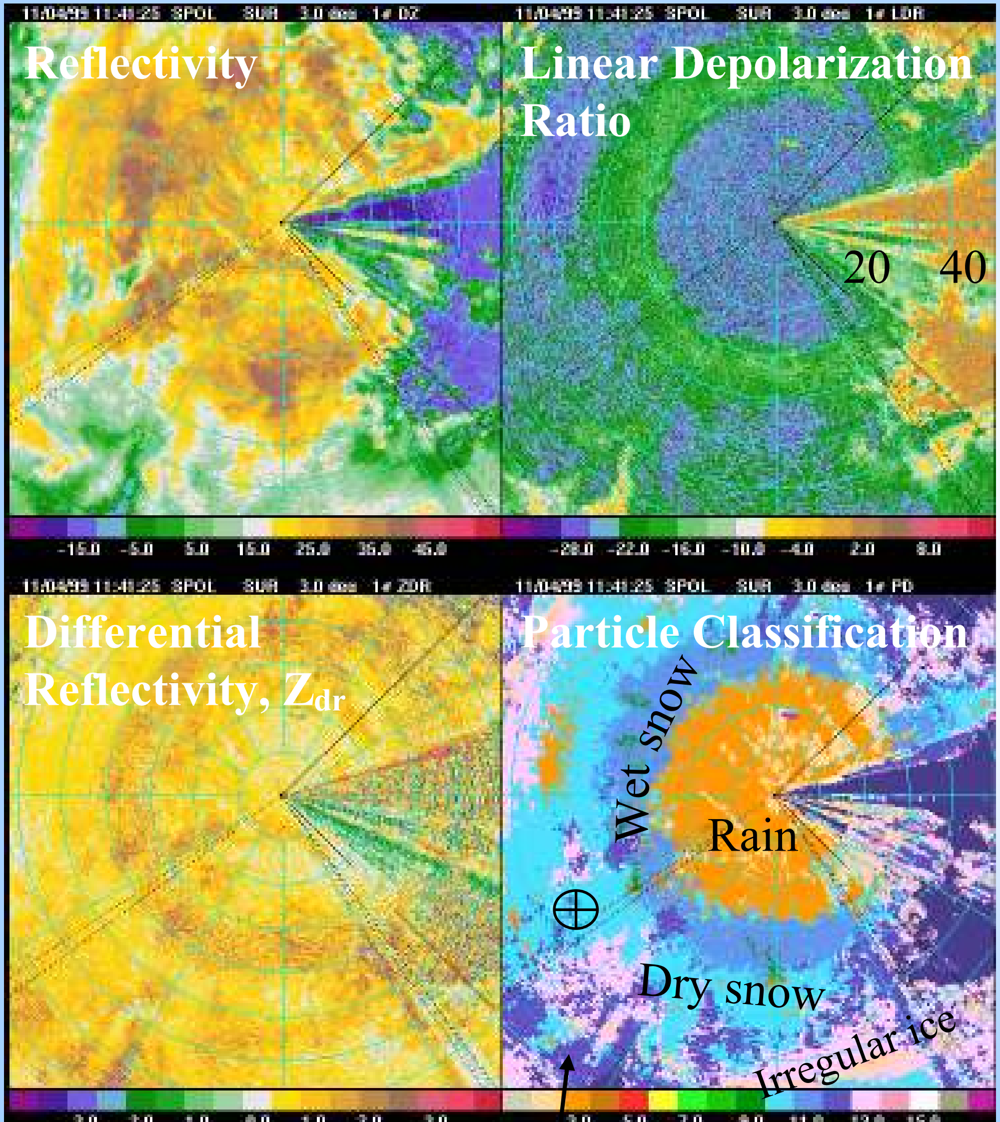


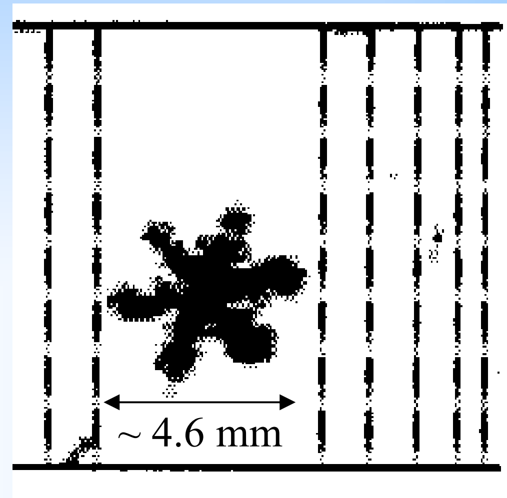


STEPS Tornadic Supercell 29 June 2000

Range-height cross section

MAP Experiment, Italy 1999





RICE – no icing occurred

PMS – crystals and aggregates

Radar – dry snow

⊕ ~ Aircraft location

Forecasting of Weather Phenomena

Thunderstorm AutoNowcast System (ANC)

Thunderstorm AutoNowcaster System (ANC)

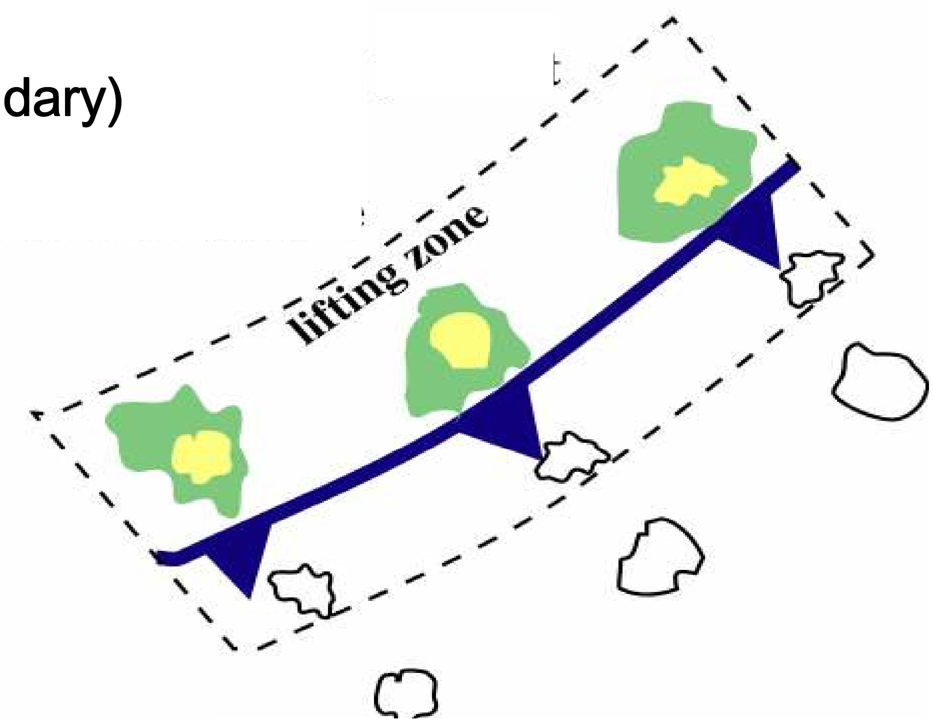
- Time and space specific forecasts of thunderstorm intensity
  - 0-2 hour time frame
  - Based on conceptual models for:
    - Storm inititiation
    - Storm growth
    - Storm dissipation
- Input data:
  - Doppler radar, mesonet, soundings, lightning, satellite, numerical model
- NOAA Aviation Weather Center
  - National Convective Weather Forecast (NCWF)

Conceptual Model (1)

Based on our present knowledge of storm evolution, the following parameters are used to forecast storm initiation, growth and dissipation.

Factors Associated With Storm Initiation:

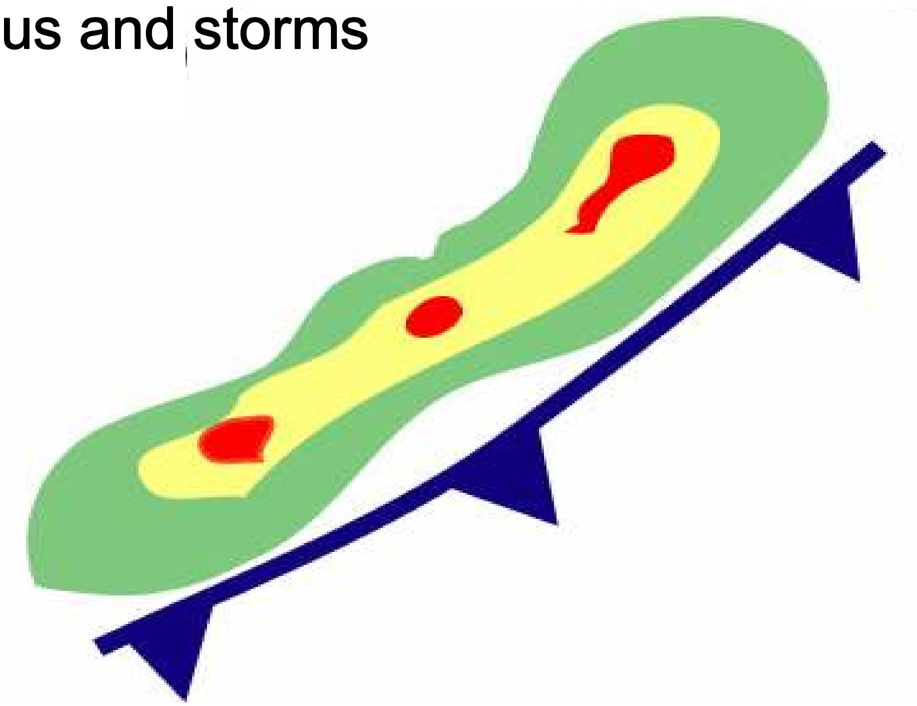
- Presence of convergence line (Boundary)
- Lifted index < 0 in lifting zone
- Cu in lifting zone
- Rapid growth of Cu in lifting zone
- Colliding boundaries
- Low boundary relative cell speeds



Conceptual Model (2)

Factors Associated With Storm Growth:

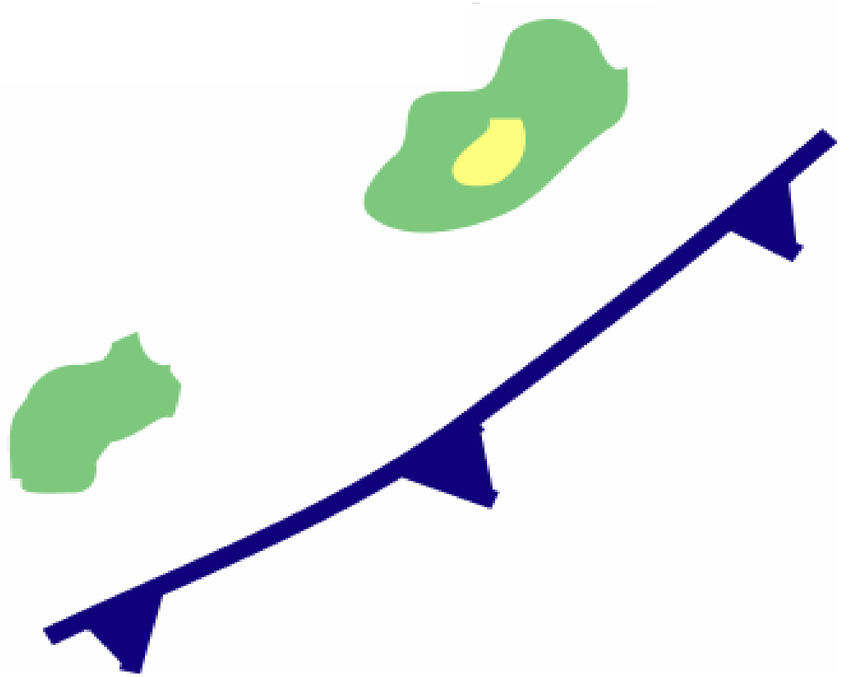
- Boundary motion = storm motion
- Convergence strong and deep
- Erect updrafts
- Merging of storms
- Boundary intercepting cumulus and storms



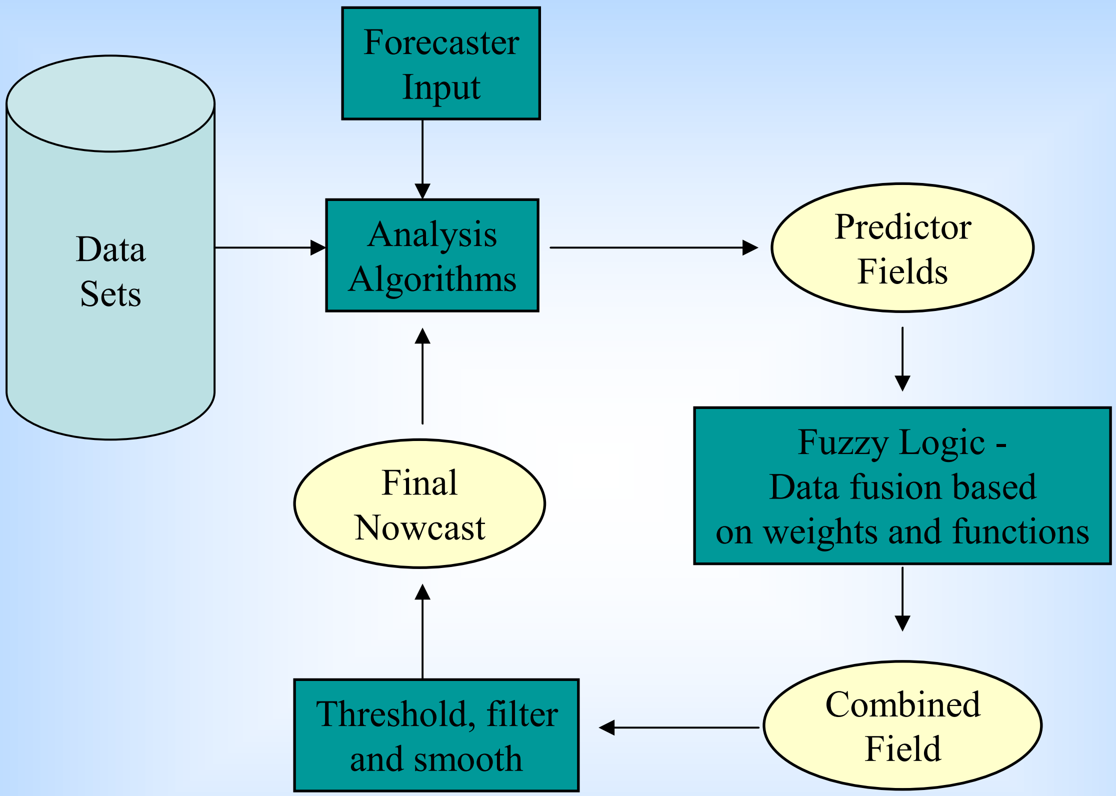
Conceptual Model (3)

Factors Associated With Storm Dissipation:

- Boundary moving away from storms
- Boundary moving into a stable region
- Storm decreasing in size and intensity
  and no boundary present



ANC Flow Chart



Nowcast Predictor Fields

- Cloud characteristics
  - satellite cloud type
  - sat. cloud growth (IR temperature cooling)
  - sat. clear sky
  - radar cumulus

- Storm Characteristics
  - position and motion
  - growth and decay rate
  - storm structure
  - storm-boundary interaction
  - precipitation accumulation

- Boundary-layer structure
  - convergence line position and motion
  - colliding boundaries
  - strength of the convergence
  - low-level shear
  - boundary-relative steering flow
  - terrain

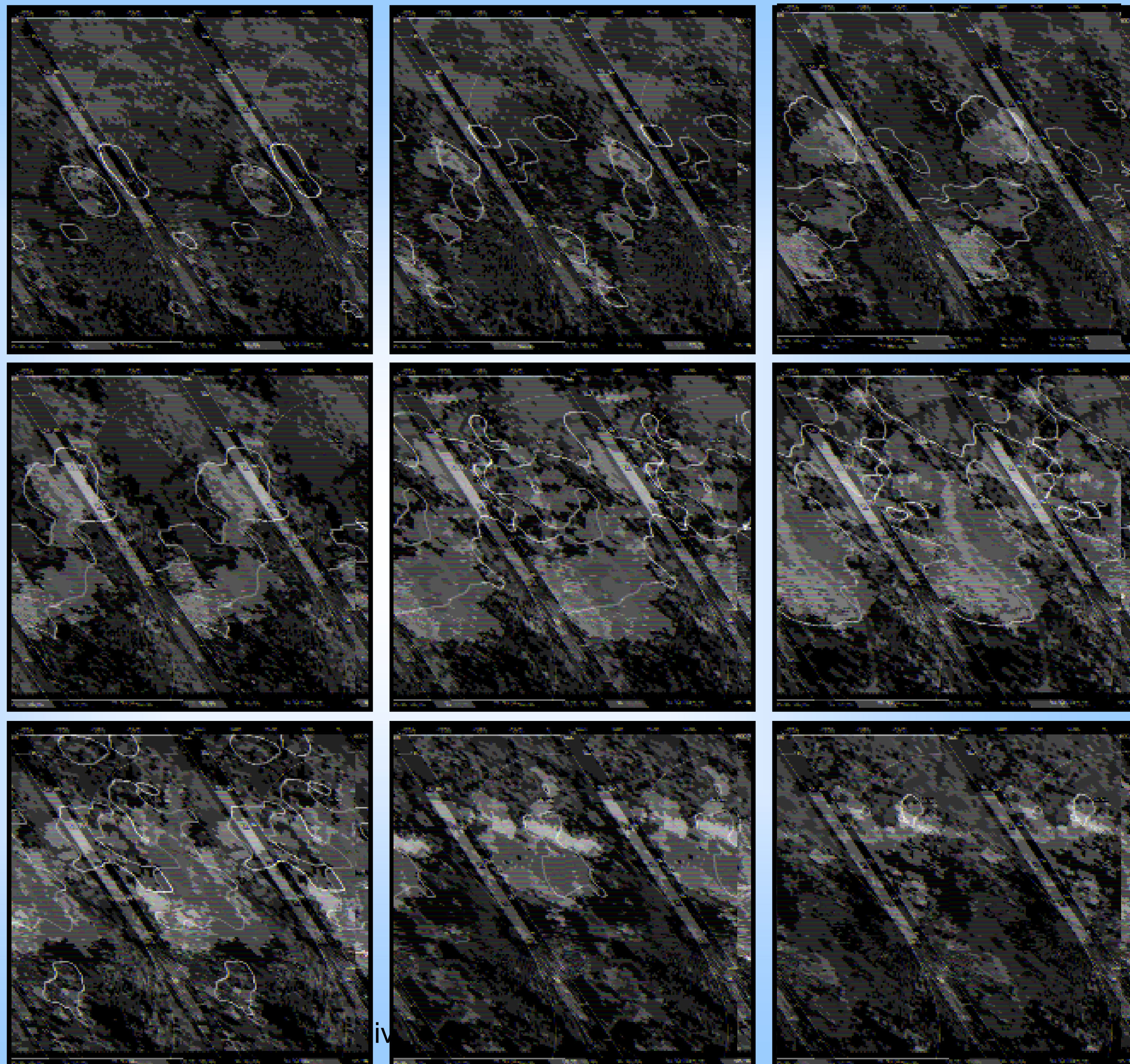
~ Predictors have different utility depending on nowcast types and time periods ~

Nowcaster

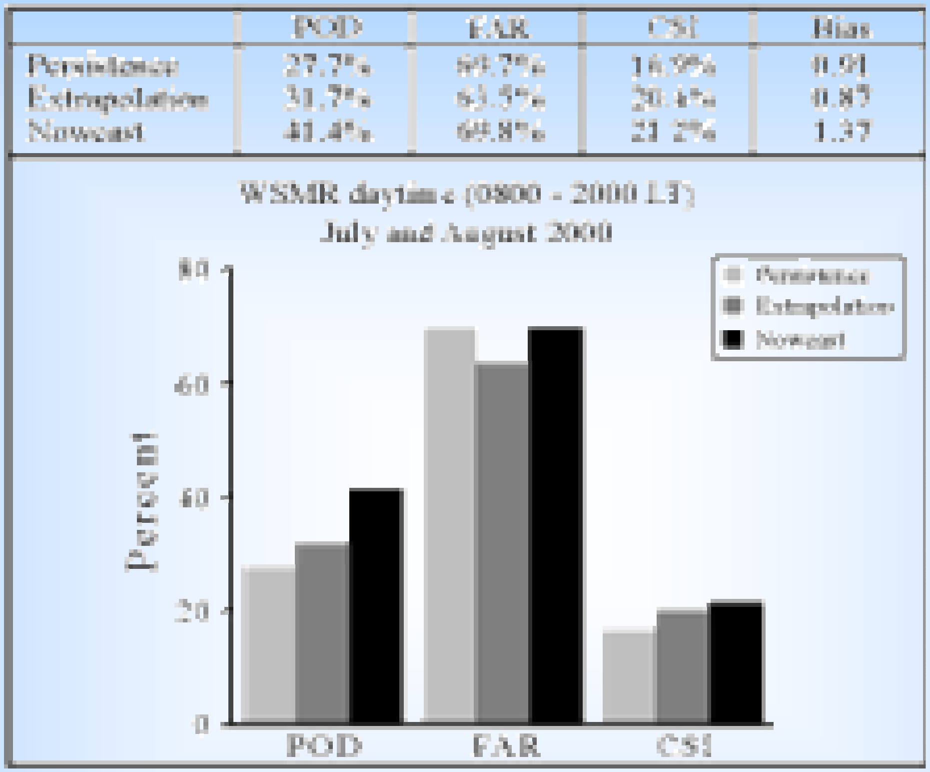
30-min Nowcast

July 5, 2001
Denver, Co

Images are at 18-min intervals



Verification Statistics



	POD	FAR	CSI	Bias
Persistence	27.7%	69.7%	16.9%	0.91
Extrapolation	31.7%	63.5%	20.4%	0.87
Nowcast	41.4%	69.8%	21.2%	1.37

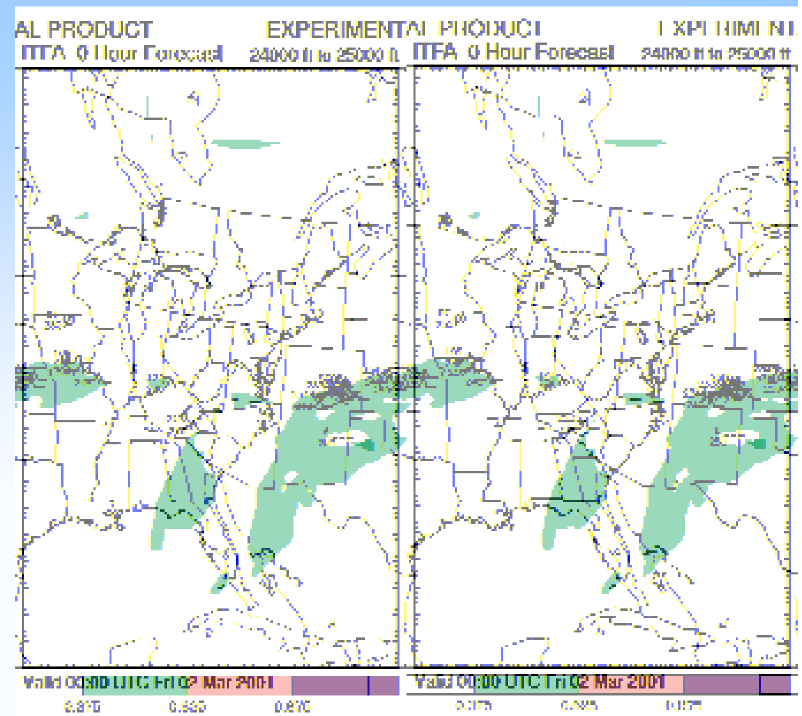
Summary statistics from July and August 2000 for White Sands, NM daytime 30-min nowcasts. The light gray, medium gray and black bars represent the persistence, extrapolation, and ANC scores respectively. The observations and nowcasts were expanded 3 km in all directions prior to the grid-to-grid comparisons.

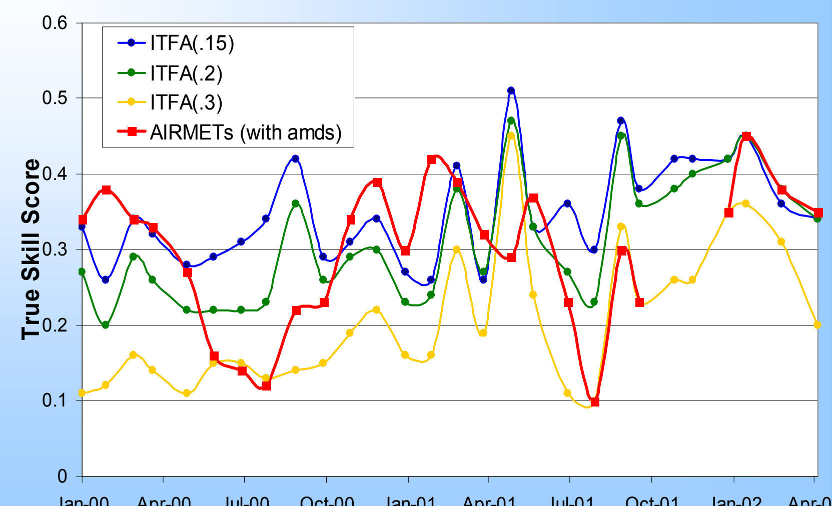
Graphical Turublence Guidance (GTG)

AI Workshop | Texas A&M University-Corpus Christi | 12-13 January 2007

GTG

- Upper level CAT prediction system
  - related to jet streams and upper-level fronts <u>only</u>
  - <u>></u> 20,000 ft <u>only</u>
  - currently working on other sources and lower levels
- Based on RUC forecasts
  - RUC domain <u>only</u>
  - 0,3,6,9,12-hr forecasts
  - updated every 3 hrs
- Fits turbulence predictors to observations (PIREPs or *in situ* reports)
- Running operationally on ADDS





GTG fuzzy logic procedure

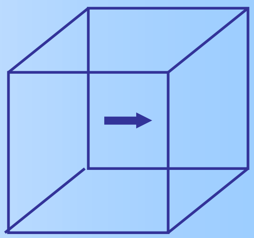
1. Compute turbulence <u>many</u> diagnostics D_i (e.g. VWS) from NWP output (e.g., RUC2, MM5) at assimilation time
2. Threshold diagnostics
3. Map diagnostics to a common turbulence intensity scale (0-1)=> D^*_i; also for PIREPs (e.g., 0.5=moderate)
4. Compare diagnostics to available observations (PIREPs) within a time window around assimilation time and above some altitude cutoff (20,000 ft):

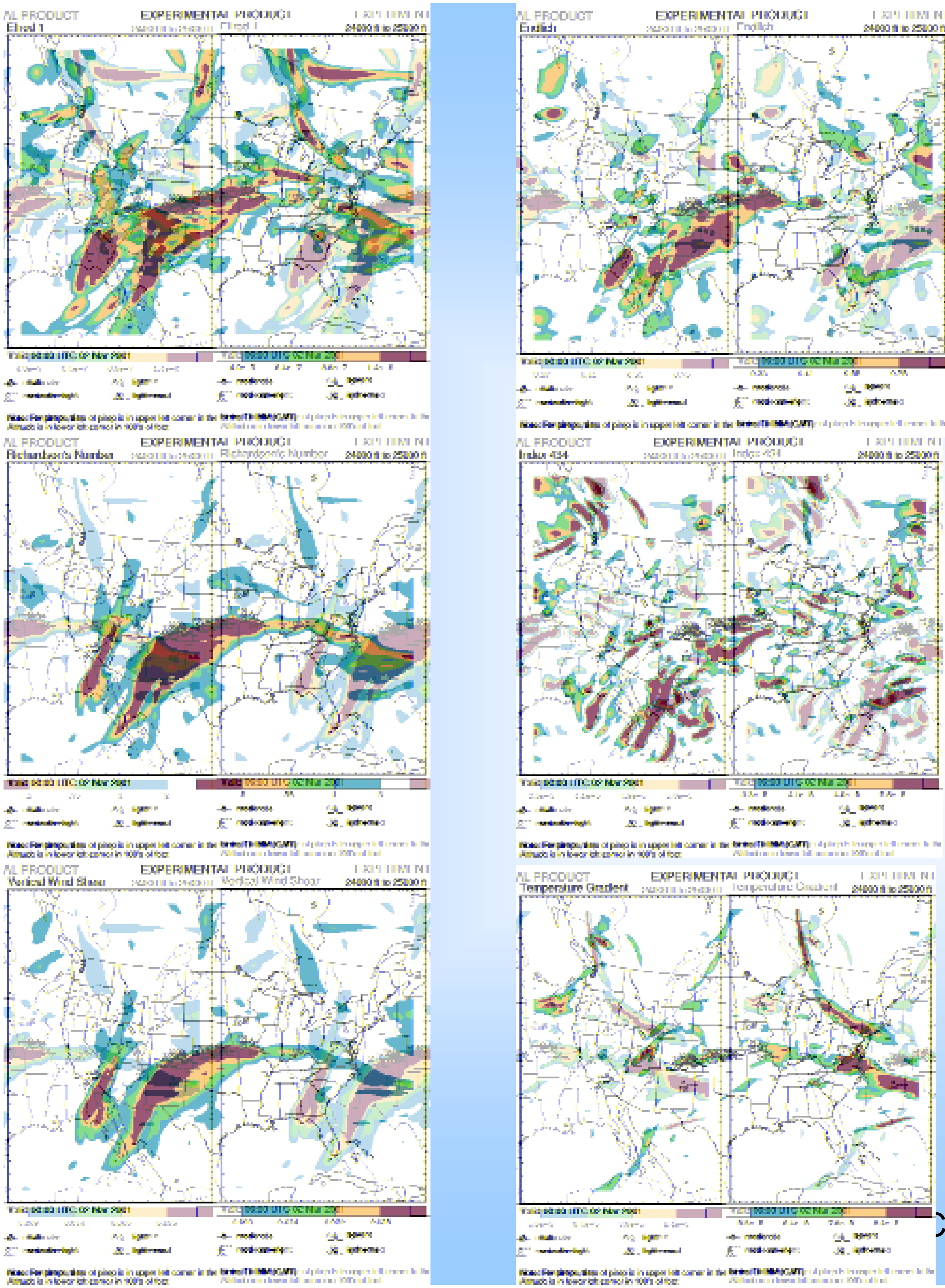
$$\text{Score}_i = \Sigma_i \{ \surd \, |I_i - P|^2 / NP \}$$

5. $W_i \propto 1/\text{score}_j$
6. Combine diagnostics and weights:

$$GTG = W_1 D_1^* + W_2 D_2^* + W_3 D_3^* + \ldots.$$

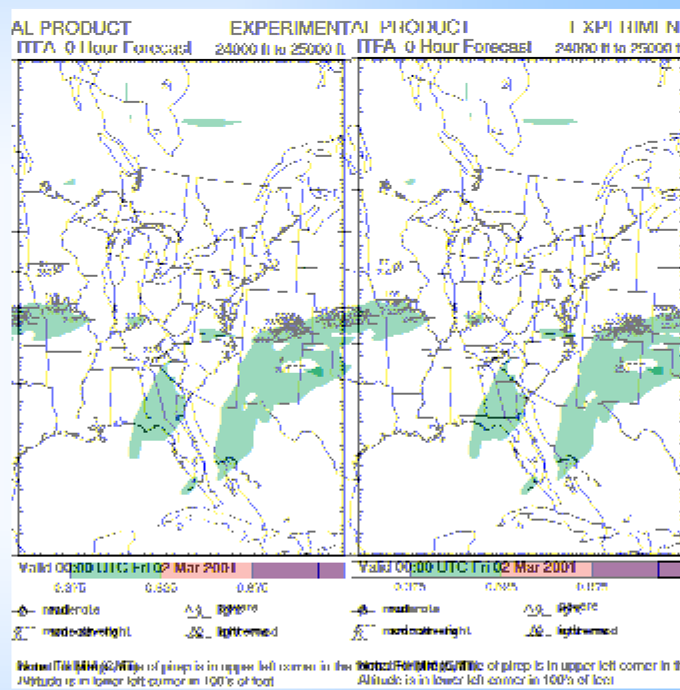
7. Use these weights for (3,6,9,12,... hr) forecasts





Example of merging diagnostics into GTG

=>



Links

- Commercial fuzzy logic software:

  http://www.mathworks.com

  http://www.wolfram.com

- Meteorological applications of Fuzzy Logic:

  www.chebucto.ns.ca/Science/AIMET/applications/

- NCAR Research Applications Laboratory:

  www.ral.ucar.edu

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