ALPHA v2.0 Status: Application of Machine Learning Technology

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ALPHA 3-Input v1.0: Deployed in Field Campaigns

Satellite

Model

3D Radar Mosaic

Find highest, coldest, thickest clouds from Total Water Path, Cloud Top Height and Cloud Top Temperature – 2D field Total Satellite Interest Find deep cloud layer,
heavy precipitation, high
condensate, updrafts,
temperature below -15°C
-3D field

Total Model Interest

Find active updrafts, high reflectivity in column along with heights of 10 and 30 dBz echo tops

- 2D field

Total Radar Interest

Calculate Total HIWC Interest

If Total Satellite Interest is > 0

Model 3D Temperature Interest * [45% Total Satellite Interest + 10% Total

Model Interest + 45% Total Radar Interest]

= Total HIWC Interest

Objective Re-Design of the ALPHA Fuzzy Logic Algorithms Using Field Campaign Data

- Fuzzy logic methodology allows for adjustment of multiple parameters in the algorithms including:
 - Input variables used
 - Shape of membership function for each variable
 - Weight given to each variable in the blending process
- Optimization of parameter set
 - Need a performance metric that defines "optimal"
 - Apply machine learning tool to our data set
 - Many iterations later, we have a new algorithm

Input Variables Considered for Use in ALPHA

| Satellite | NWP Model | Groundbased Radar |
|---|--|--|
| Effective Cloud Top Temperature | Temperature | Maximum Reflectivity in Column |
| Effective Cloud Top Height | Surface Precipitation | Maximum Height of 30 dBz Reflectivity |
| Total Water Path | Total Condensate | Maximum Height of 10 dBz Reflectivity |
| Optical Depth | Total Water Path | Vertically Integrated Liquid |
| Brightness Temperature Difference (6.7 – 10.8 um) | Vertical Velocity | Volume Averaged Height Integrated Reflectivity |
| Brightness Temperature Difference (10.8 -12 um) | Tropopause Height | Precipitation Ice Mass |
| | Convective Available Potential Energy, Convective Inhibition | |
| | Divergence/Convergence | |
| | Vorticity | |

Methods/PSO Summary

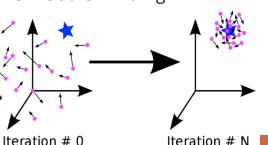
Used a "Particle Swarm Optimization" to optimize membership functions and weights

- Stochastic, supervised machine learning algorithm
- Tests sets of parameters for performance and automatically adjusts them to get progressively better performance
- Objective way to choose ALPHA membership functions and weights
- Works in any number of dimensions

Particle Swarm Optimization (PSO)

- Supervised machine learning algorithm to find optima
- Easily to implement in any number of dimensions
- Each "particle" in the swarm "remembers" where it and its neighbors have been
 - The location of a particle represents a set of parameters by which we could compute HIWC interest
 - Particles move stochastically towards better solutions while searching the space around them
 - Eventually the particles converge on a local optimum

 Running several times increases likelihood of finding the global optimum



Update the position and velocity for all the particles No Termination condition satisfied? Yes Output gbest (best position for all the particles) End Iteration # N

Start

Input parameters, initialize the position and

velocity for all the particles

Calculate the objective function value and fitness

function value for all the particles

Update pbest (best position for each particle),

Update gbest (best position for all the particles)

PSO Implementation

3 degrees of freedom per input field

- Location of first inflection point
- Distance between inflection points (enforced to be positive)
- Weight (enforced to be positive and sum to 1)

Membership functions are piecewise linear with exactly 2 inflection points

Sign of each membership function also determined by user

PSO can remove inputs by assigning zero weight, but cannot add new inputs

Radar, satellite, model, and temperature interests optimized separately

Blended using weights from another PSO

Optimization Metrics Tested

The PSO algorithm needs to know how to score each location so that it can determine how the particles should move in each iteration. We tried several metrics:

- 1) Correlation between IWC and interest
- 2) **Histogram Error** where we bin interest values, look at sum of squared difference from an "ideal" histogram where interest = fraction of MOG IWC measurements
- 3) Fraction of Correct assignments using a 0.5 IWC and 0.5 interest thresholds
- 4) Sum of PoDno and PoDyes using 0.5 IWC and 0.5 interest thresholds
- 5) **Products** developed to try to balance two or more of the other metrics at once
 - (1 correlation)*(histogram error)*(fraction of wrong assignments)
 - (1 correlation)*(histogram error)*(2 PoDyes PoDno)

Choice of Metric

The **correlation** between IWC and interest was the preferred metric

- Utilized the most information
 - No need to bin or categorize the IWC or the interest
 - All of the other metrics relied on defining bins or thresholds for IWC and/or interest, so some information is lost in the process of doing this
 - Many other metrics put a lot of weight on just a handful of inputs
- Can still look at histogram shape and PoD statistics after running
 PSO for further verification

ALPHA 2.0 Summary

All membership functions and weights adjusted based on "training" with IWC data from IKP2 Satellite Interest

- Incorporate two new brightness temperature difference fields
- Replace total water path with optical depth

Radar Interest

- Remove 30 dbz height
- Add new VAHIRR field (volume averaged height integrated radar reflectivity)

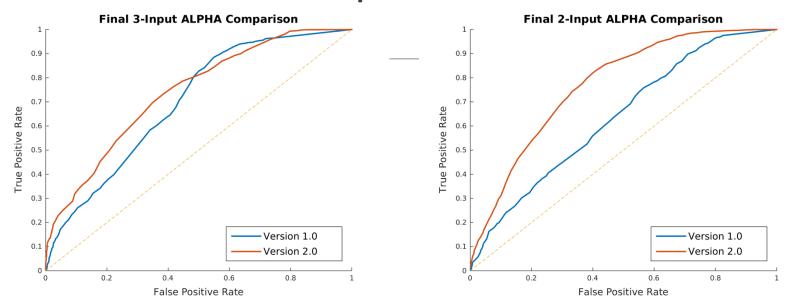
Model Interest

- Remove total water path and precipitation
- Add surface wind curl and divergence
- Only permitted to increase final interest

Temperature Interest

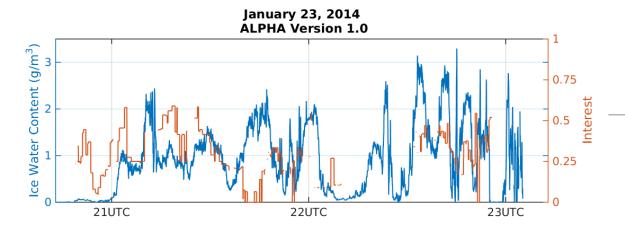
Include warmer temperatures

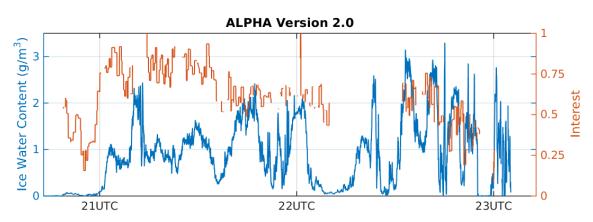
Performance Comparison



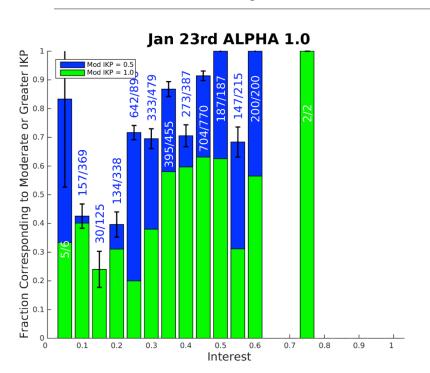
These ROC curves are created by setting a constant HIWC threshold of 0.5 g/m³ and letting the HIWC interest threshold vary between 0 and 1

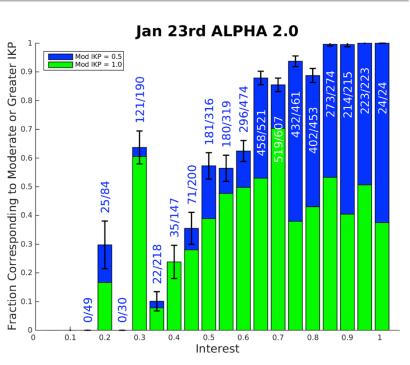
Note: The 3-Input interest has a much smaller sample size than the 2-Input. If we only consider point where both interests are available, the 3-Input performs better than the 2-Input interest.



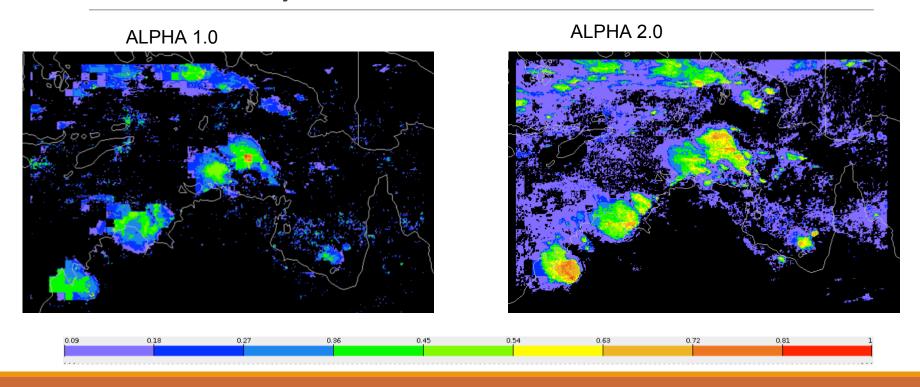


Case Study: Jan 23rd Darwin Flight





Case Study: Jan 23rd 2015, 22:45 UTC



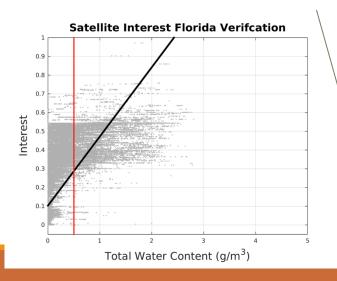
Florida Verification: Satellite

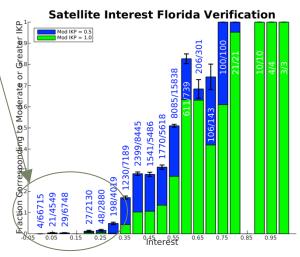
Stronger correlation between interest and IWC than training set (Darwin and Cayenne)

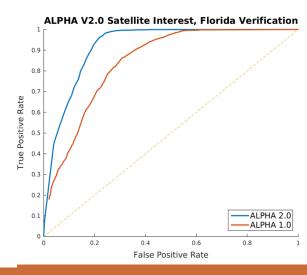
- Florida satellite correlation: 0.6671
- Training set satellite correlation: 0.4394

Few interest values above ~0.55

Very few false negatives







Next Steps with ALPHA v2.0

- Continue with comparison of ALPHA product with IKP2 IWC measurements from HIWC-Florida experiment
 - Independent assessment
- Update ALPHA-CONUS real-time product with ALPHA v2.0; implement a version in Australia
- Use ALPHA v2.0 to characterize horizontal variation and time duration of HIWC features in ALPHA products
- Airborne cloud radar (RASTA) IWC retrievals for comparison with ALPHA vertical variation
- Advection of HIWC features using TITAN (Thunderstorm Identification Tracking and Nowcasting)

Planned presentations and publications

AMS ARAM Conference - Jan 2017

- 1. Haggerty, Rugg, McCabe, Kessinger, Strapp, Potts, Palikonda: Detection of High Ice Water Content (HIWC) conditions: Status of nowcasting tool development for avoidance of ice crystal icing events, submitted.
- 2. Rugg, Haggerty, McCabe, Kessinger, Strapp, Delanoe: Evaluation of the Algorithm for Prediction of High Ice Water Content Areas (ALPHA): Methods and Results, submitted

AIAA Atmosphere and Space Environment Conference - June 2017

1. Rugg, Haggerty, Palikonda, Potts: High Ice Water Content Conditions around Darwin: Frequency of Occurrence and Duration as Estimated by a Nowcasting Model, submitted.

Journal Articles in Preparation

- Haggerty and HIWC co-authors: Development and Verification of a Detection Method for High Ice Water Content Regions, planned submission to an AMS journal, early 2017
- Haggerty, Jensen, and Yost: High Ice Water Content and Airborne Temperature Measurement Anomalies near Tropical Convection, planned submission to an AMS journal, early 2017

Additional Slides

ALPHA 2.0: Temperature Interest

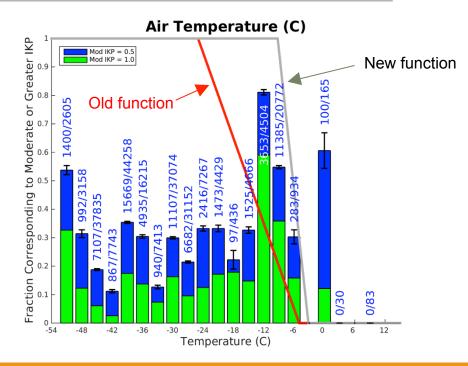
The blended interest is multiplied by the temperature interest to mask out areas too warm for HIWC

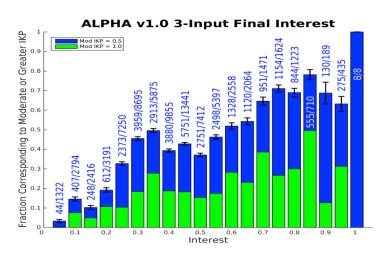
PSO runs resulted in a membership function that includes warmer temperatures

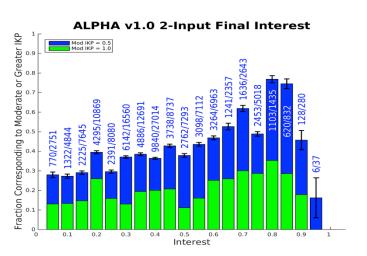
Big improvement in final ALPHA performance between old and new membership functions

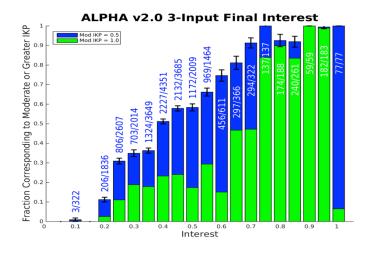
Little difference in performance between new algorithm and using no temperature masking

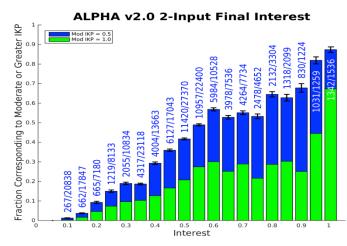
- Sampling bias
- Likely prevents over-forecasting in above freezing temperatures

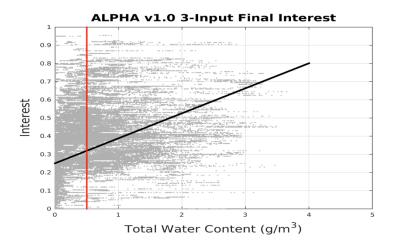


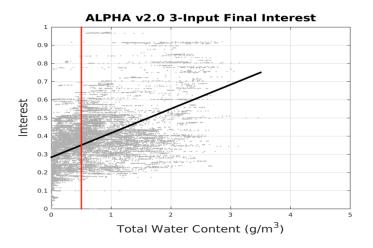


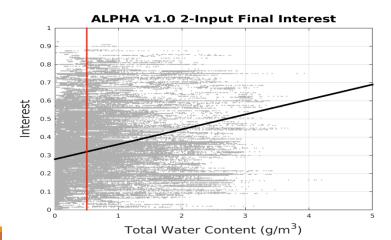


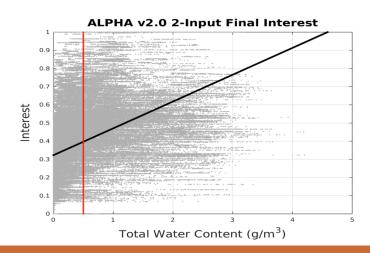




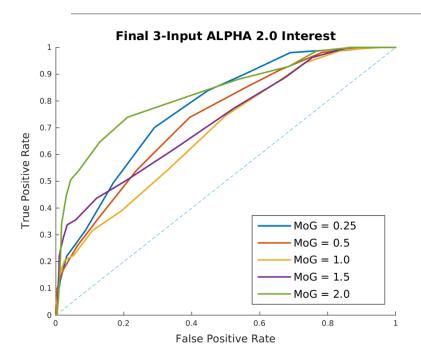


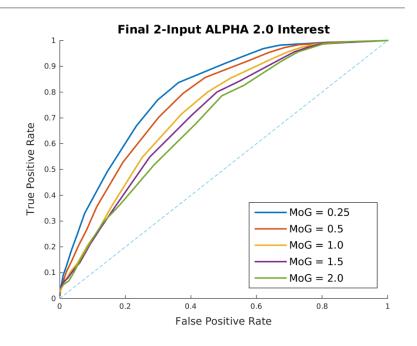






V2.0 Performance by IWC Threshold





Brightness Temperature Differences

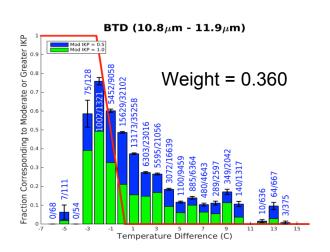
Assigned high weight in ALPHA 2.0 satellite interests

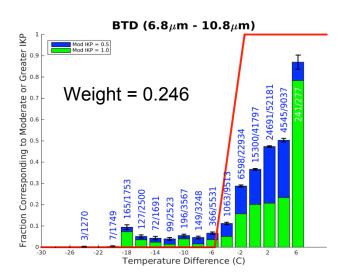
Over 60% combined

Water vapor minus infrared (right)

- Indicates moist stratosphere
- Associated with overshooting tops

Two different infrared channels (below)





Schmetz, J., S. A. Tjemkes, M. Gube, and L. Van De Berg. "Monitoring Deep Convection and Convective Overshooting with Meteosat." *Adv. Space Res.* 19.3 (1997): 433-441.