

Using Spatiotemporal Relational Random Forests (SRRF) to Predict Convectively Induced Turbulence

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Image Courtesy: New York Times

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Convectively Induced Turbulence (CIT)

- Generated by air flow asymmetries
- Occurs near and around thunderstorms
 - Effect of large scale convection
- Like clear-air turbulence, invisible (not in cloud)

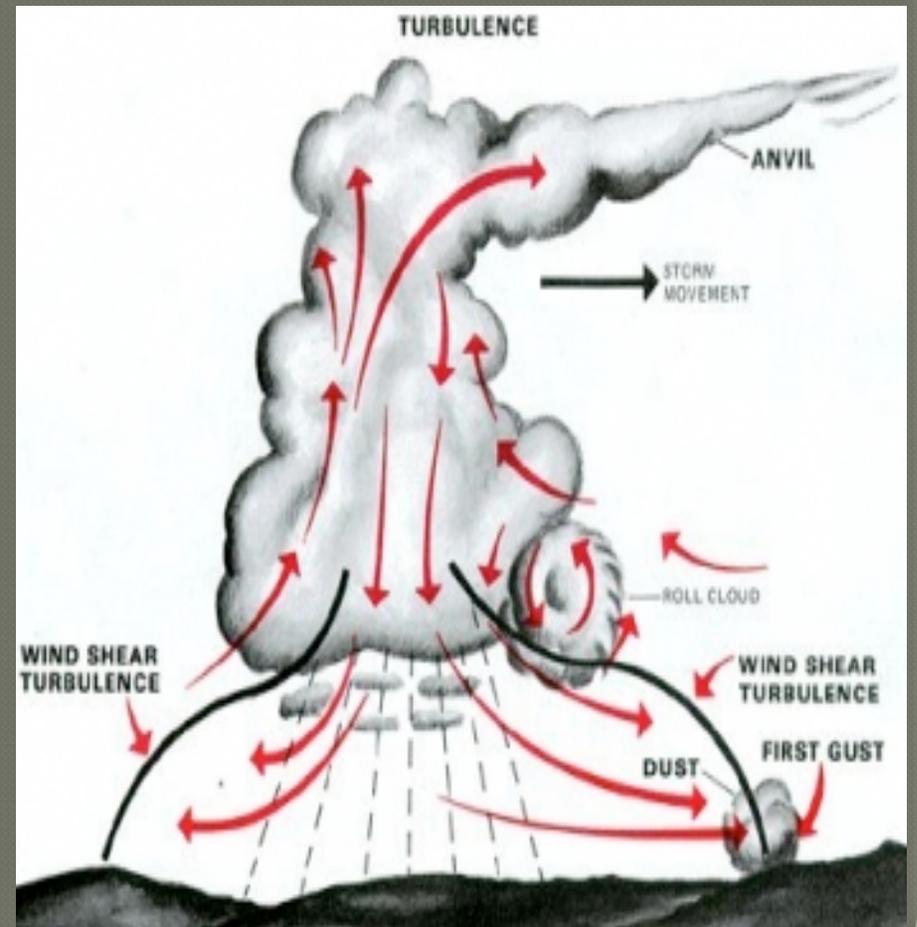


Image Courtesy: www.yalibnan.com

Why better predict CIT? (Applications)

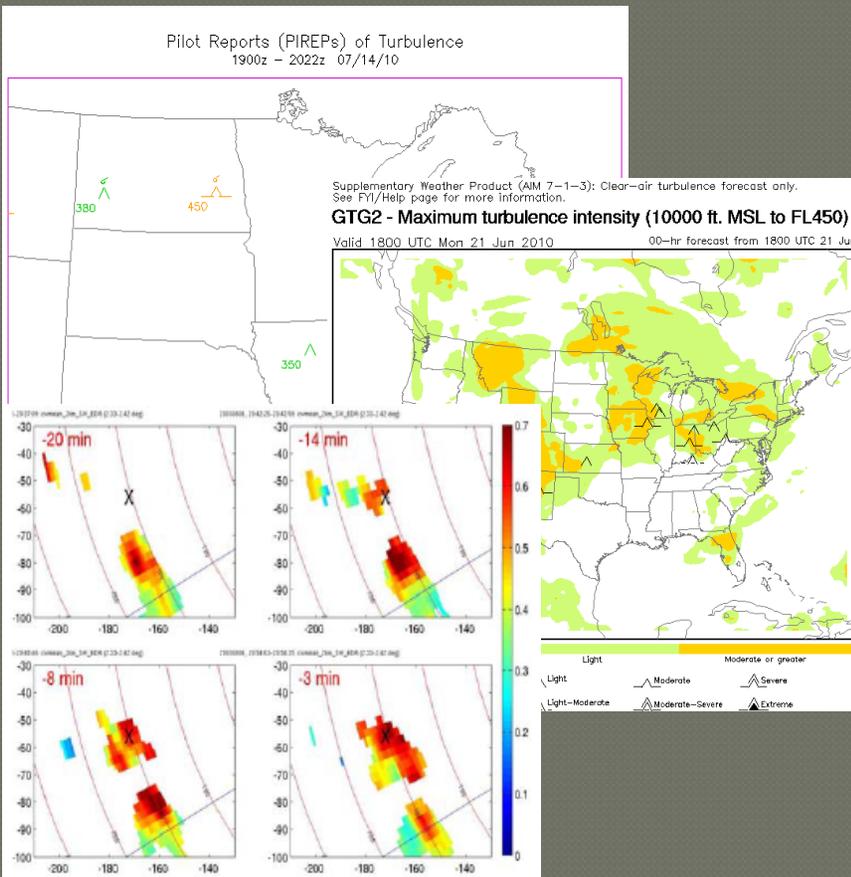
- Turbulence is a major hazard for aviation
 - Delays in flight
 - Structural damage to aircraft
 - Injuries to passengers
 - Fatalities
 - Airline economics
- Current FAA guidelines for CIT:
 - Don't attempt to fly under a thunderstorm
 - Avoid severe storms by at least 20 miles
 - Clear the top of known severe thunderstorms by at least 1000 feet for each 10 kt of wind speed at the cloud top
 - Be warned of thunderstorm tops in excess of 35,000 ft
 - Better understanding of turbulence allows for better avoidance of these hazards



Image Courtesy: www.wildlandfire.com

Information from: Williams, et al. *A Hybrid Machine Learning and Fuzzy Logic Approach to CIT Diagnostic Development*. (Currently Unpublished)

Current Turbulence Prediction Methods and Limitations



- Pilot Reports (PIREP)
- Graphical Turbulence Guidance (GTG)
- NCAR Turbulence Detection Algorithm (NTDA)

Images Courtesy of www.aviationweather.gov, Williams et al. (2004)

Current turbulence prediction enhancements at NCAR

- Diagnose Convectively-Induced Turbulence (DCIT)
 - Regular random forests trained to create a turbulence prediction on most current data
 - Trained random forests create a prediction at each grid point over CONUS where data is available
 - Final product is a snapshot of turbulence locations
 - Updates every 15 minutes
 - Deterministic: gives a turbulence measurement value at each point

Current turbulence prediction enhancements at NCAR (2)

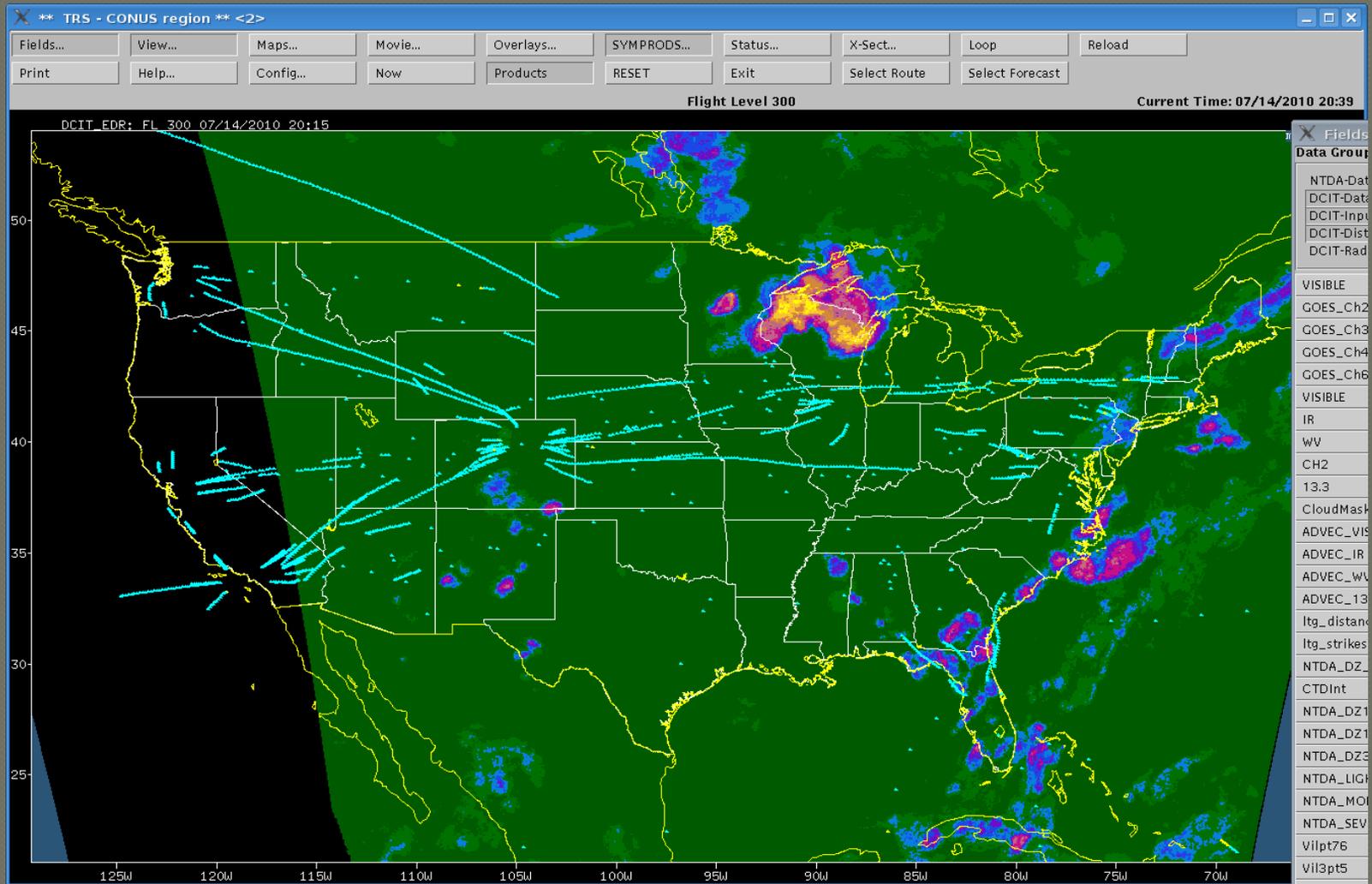


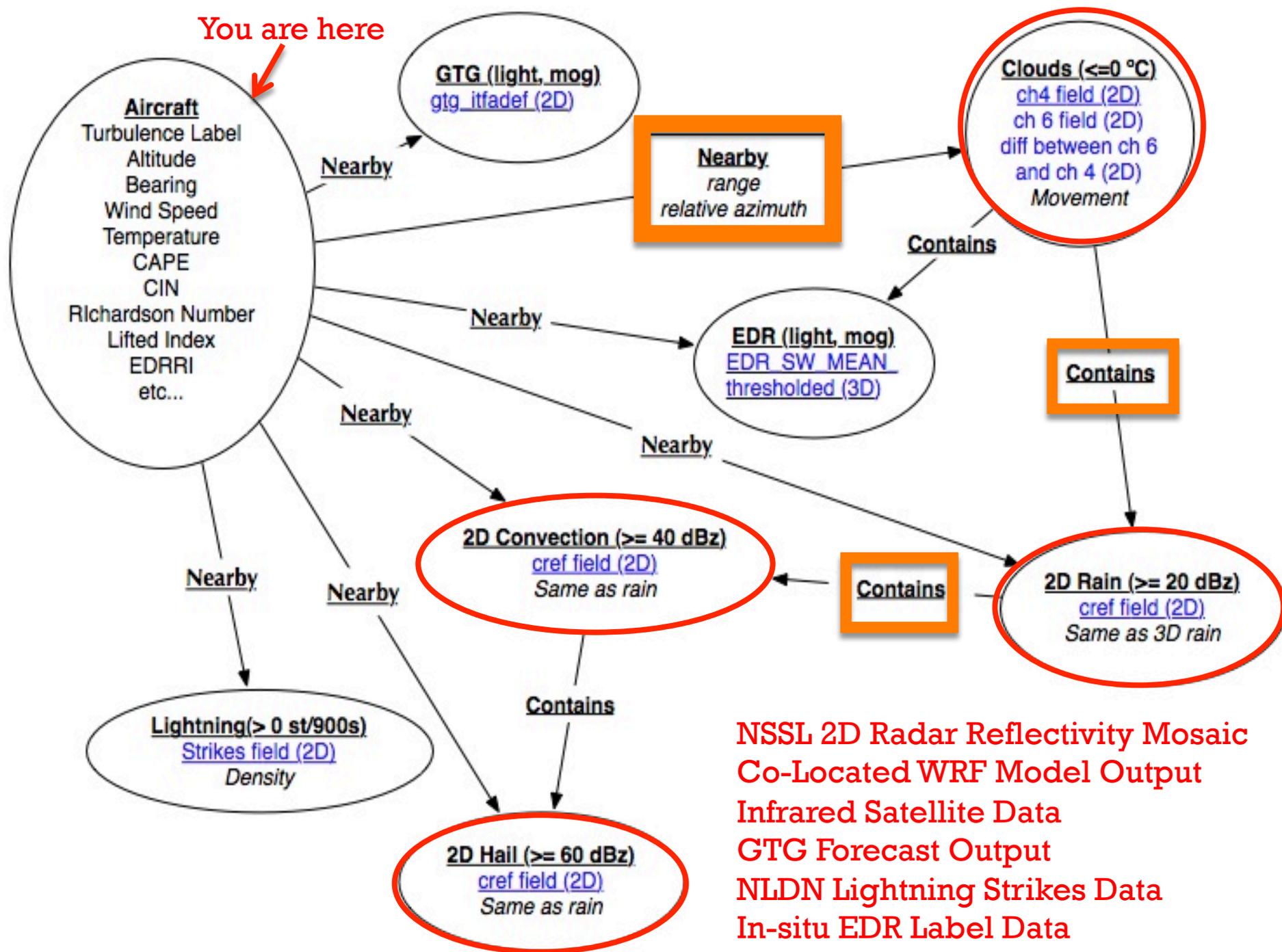
Image Courtesy: Jennifer Abernethy (NCAR/RAI)

Our Approach

● Spatiotemporal Relational Random Forests (SRRF)

- Object-oriented
 - Rain, convection, hail, lightning, vertically integrated liquid (VIL), clouds, aircraft, EDR
- Relations
 - SRRF's work SPATIALLY and TEMPORALLY
- Allows us to follow patterns as they emerge and change
- Aircraft centric
 - Within 40 nautical miles, above 15,000 feet
- Probabilistic prediction that turbulence may occur

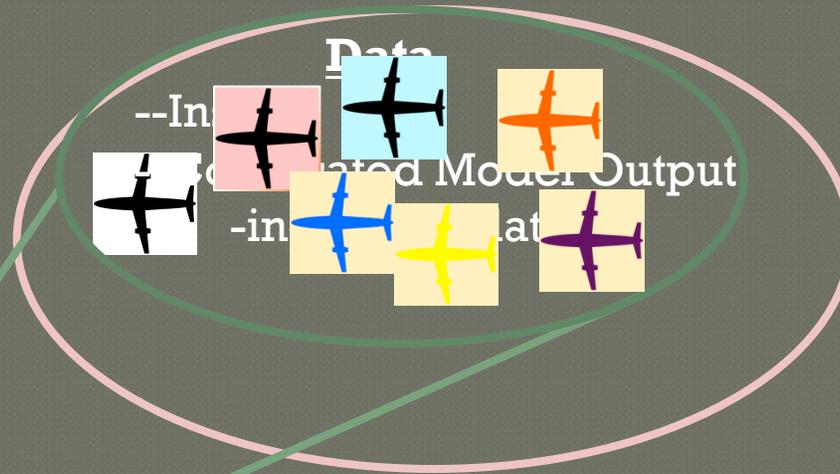




NSSL 2D Radar Reflectivity Mosaic
Co-Located WRF Model Output
Infrared Satellite Data
GTG Forecast Output
NLDN Lightning Strikes Data
In-situ EDR Label Data

How do SRRFs work?

Chosen aircraft that flew on March 10, 2010



Training Set

Randomly choose N questions:

Chose best split based on chi squared:



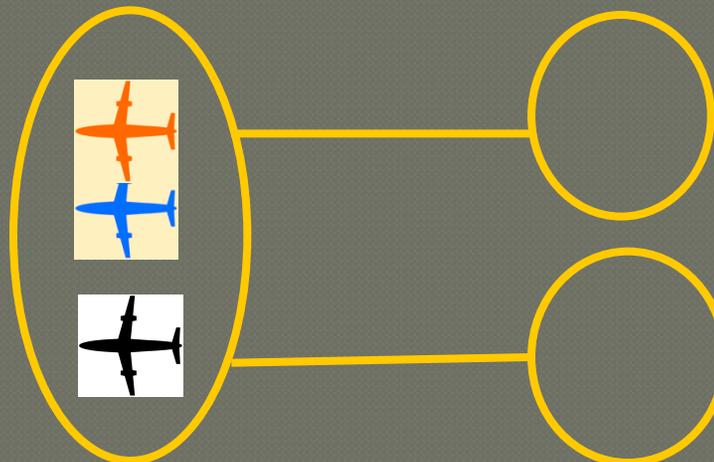
Is rain above 60 DBZ and nearby lightning?

Is cloud coverage 90% and contained with rain?

Is hail occurring 15 minutes prior and within convection?

Is cloud coverage 90% and contain rain?

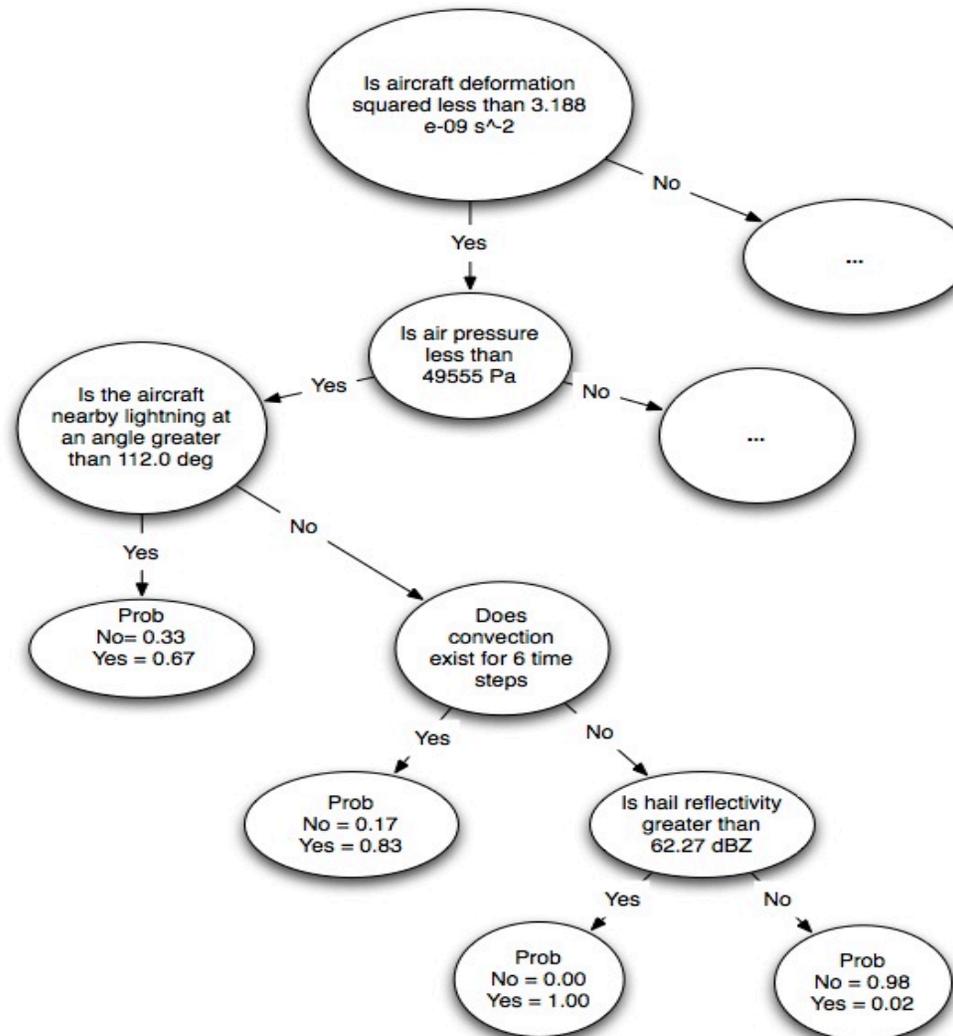
Split Instances Accordingly
(Recursive)



Turbulence:
Yes

Turbulence:
No

Example Tree



The Forest

- Send the rest of instances down the tree
- Redo for multiple trees- A FOREST
 - Collect votes
- Repeat creation of forest 30 times
- Verification
 - Skill scores
 - Variable importance
 - Error estimation

Results

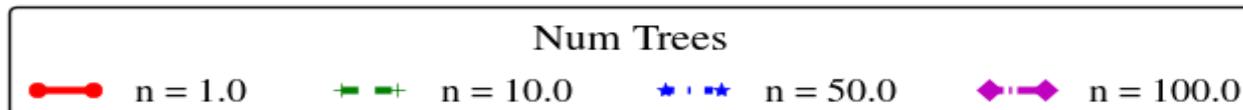
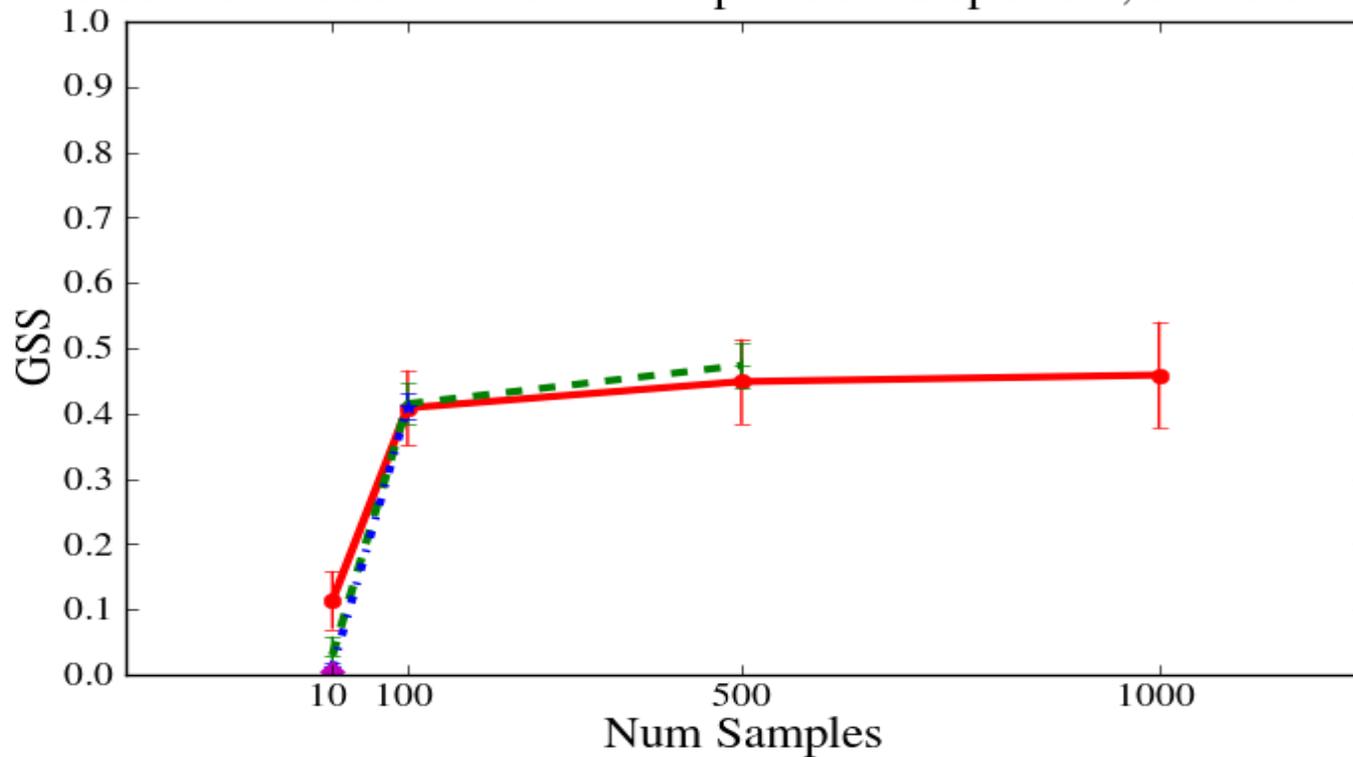
- Nulls under-sampled by 99% initially
- 30 runs of every combination of each of the following:
 - Samples (# questions at node): 10, 100, 500, 1000
 - Number of trees per forest: 1, 10, 50, 100

Experiment Set #1

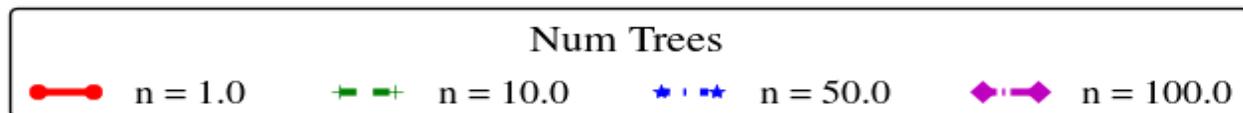
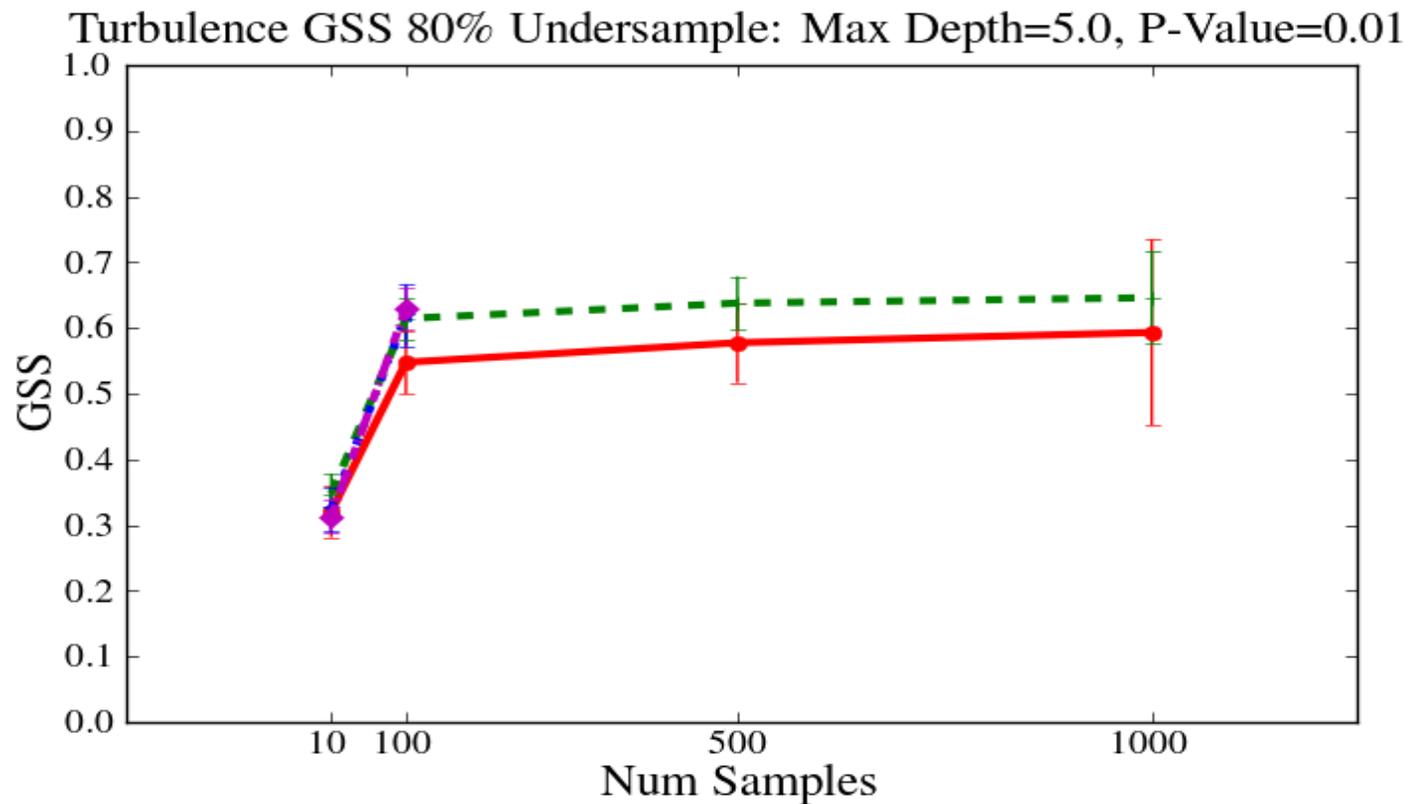
- ④ 49 Days: March 10 – April 28, 2010
- ④ Effect of under-sampling the training set
 - Helps to further balance null vs. MOG
 - Does not effect testing set
 - 3 under-sampling levels: 40%, 60%, 80%

Performance (Gerrity Skill Score)

Turbulence GSS 40% Undersample: Max Depth=5.0, P-Value=0.01



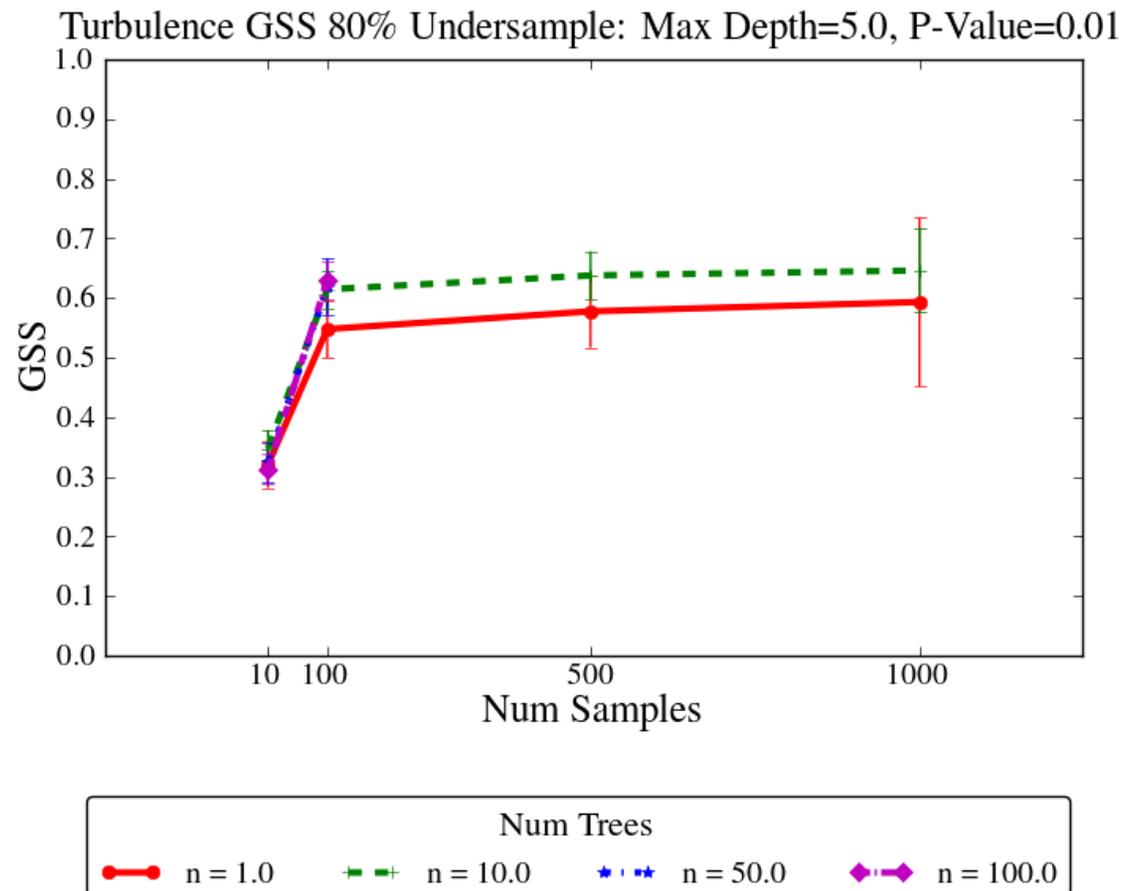
Under-sampling Effect



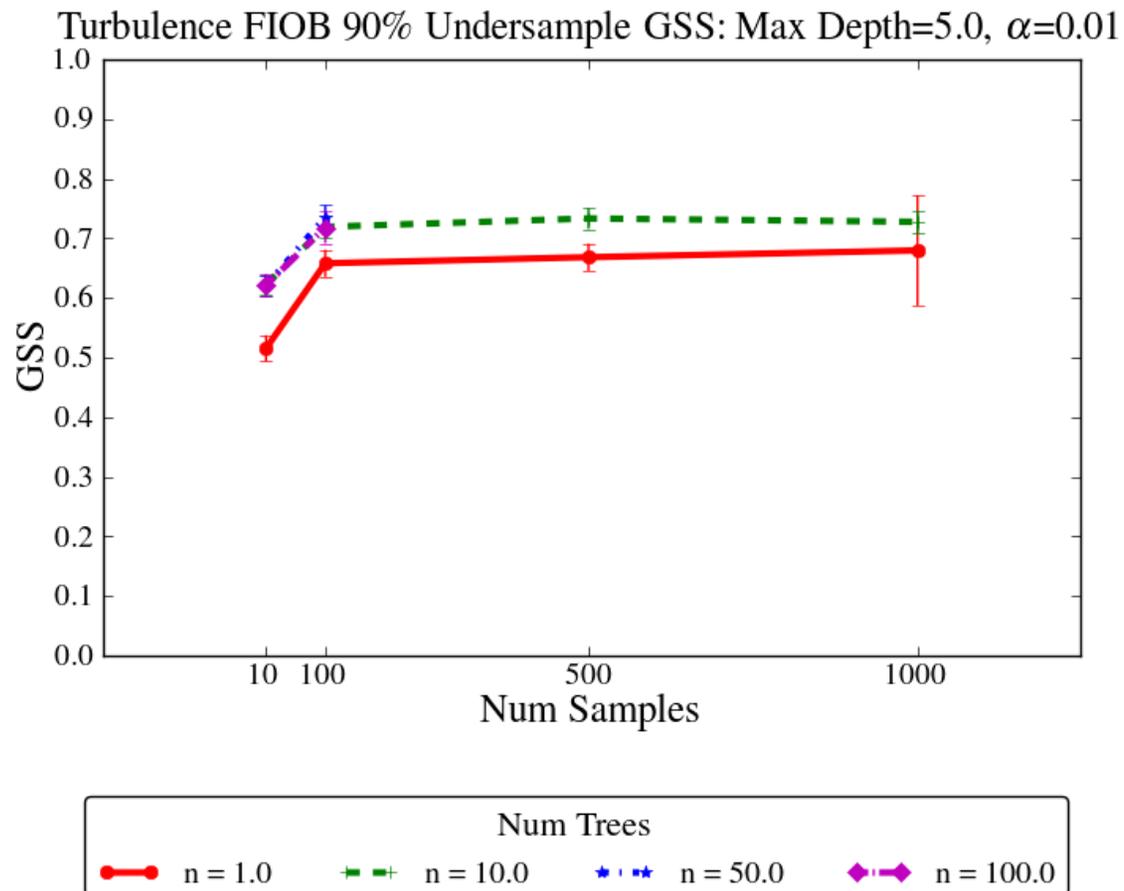
Experiment Set #2

- ⦿ 3 months: March 11 – June 10, 2010
- ⦿ Effect of training with more data
- ⦿ 90% null drop on training set

Previous Experiment



Same Experiment with 3 months of data and 90% under-sampling



Performance of Best Tree

	Obs.	Turbulence	Null
Forecast			
Turbulence		5787	62
Null		554	376

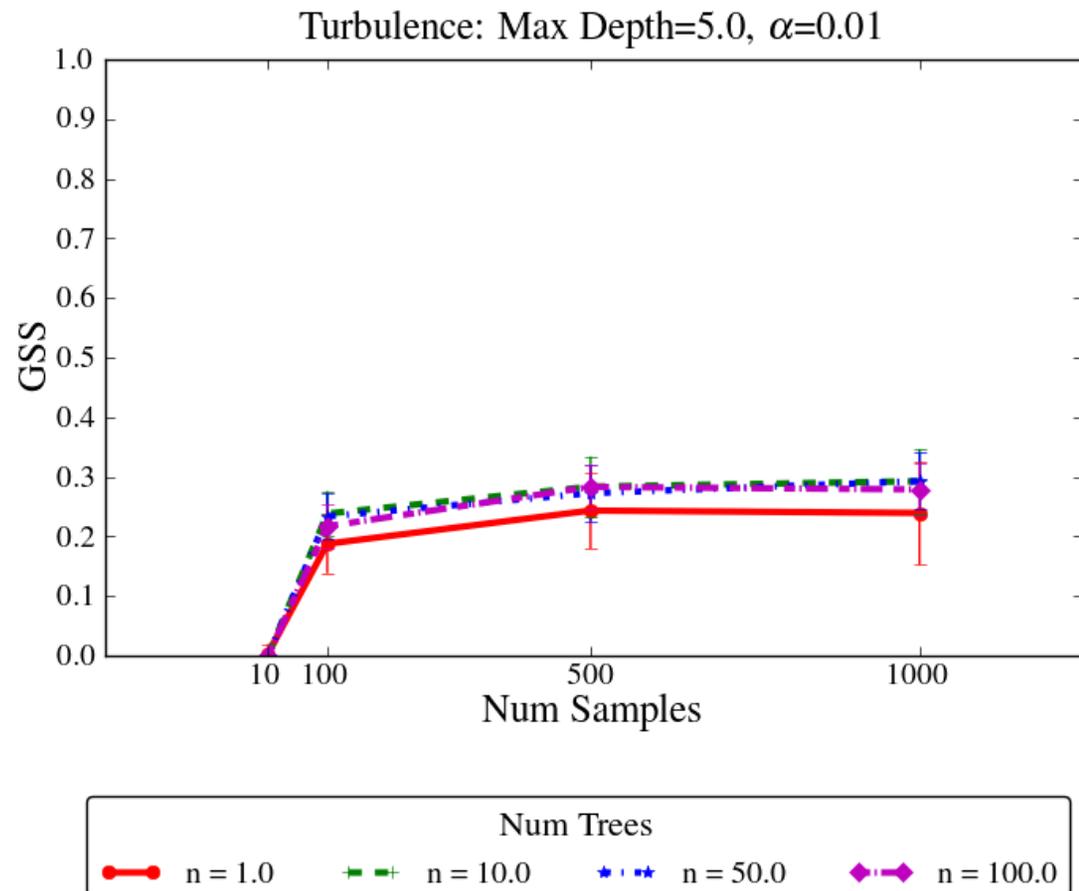
TSS: 0.771 = POD = 0.9126
FAR = 0.1060
POFD = 0.1416

Compare to Worst Tree TSS: 0.219

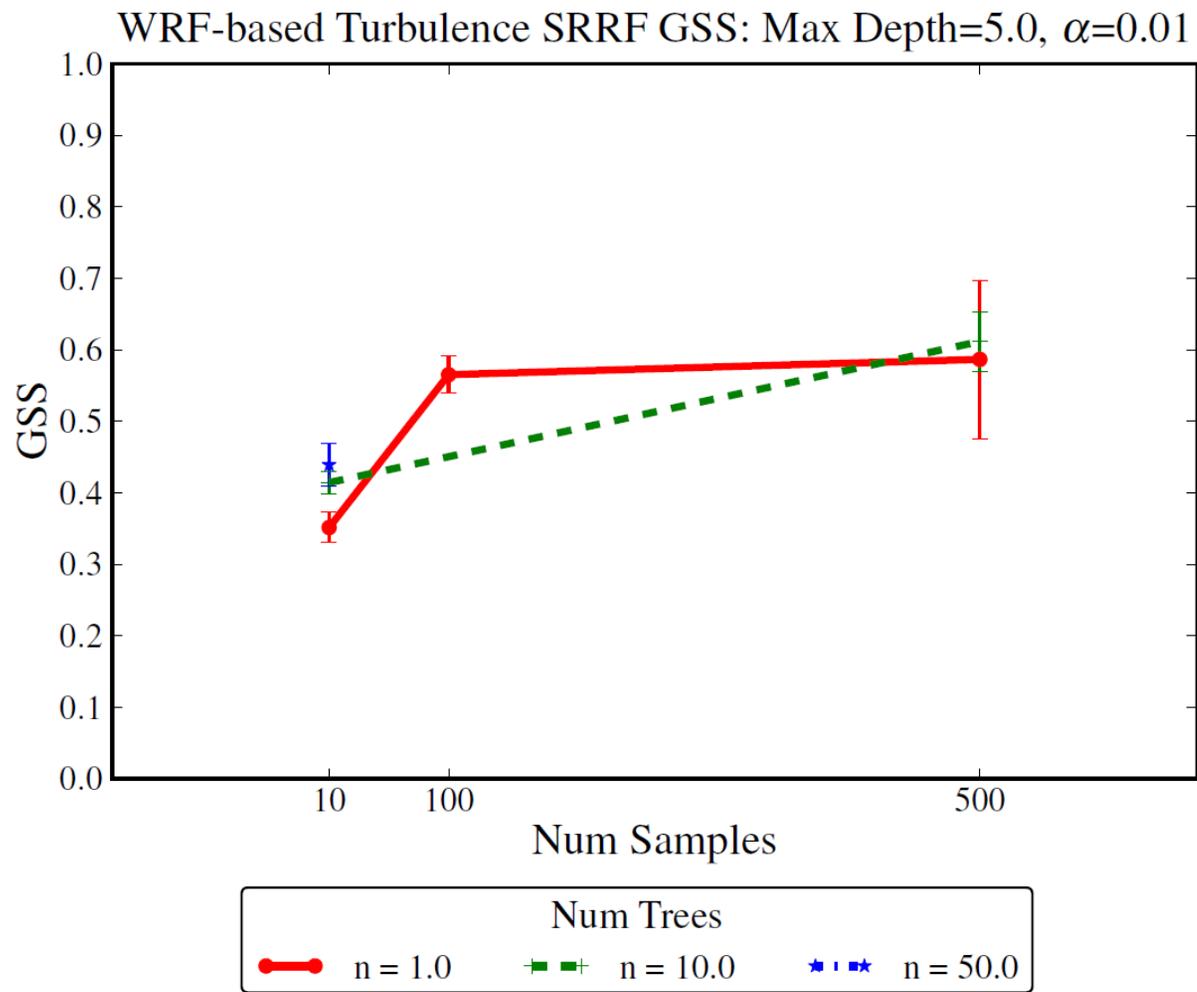
Experiment Set #3

- ◉ Older experiments used RUC data
- ◉ Current experiments use WRF-RR version 1 data
- ◉ Does data source make a difference?
- ◉ Experiment Setup
 - Schema of WRF-RR data is modified to match the RUC data experiments as closely as possible
 - Certain variables are ignored

RUC -based Performance



WRF-based Performance



Importance analysis

Predictors	Mean Z-Score	Standard Deviation
Aircraft:Frontogenesis Function	1.130	0.341
Aircraft:NC State Index 1	0.733	0.189
Aircraft:Temperature	0.722	0.281
Aircraft:EDR/Richardson Number	0.575	0.354
Aircraft:MSL Pressure	0.569	0.377
Aircraft:Total Deformation Squared	0.526	0.258
Aircraft:Pressure (at flight level)	0.510	0.207
Aircraft:Geopotential Height	0.495	0.192
Aircraft:Smoothed Pressure	0.490	0.286
Aircraft:Altitude (ASL)	0.447	0.168

- Importance determined by permuting each predictor's value, and seeing how the overall prediction performance of the forest changes due to this randomization
- Specific to 30 runs, 10 trees, 500 samples, 0.8 under-sampling

Summary

- SRRF gives us the ability to create spatially and temporally varying objects
- In addition, relations allow us to follow how objects interact
- Gives us the unique ability to determine important features in terabytes of data fairly quickly
- Results can offer suggestions as to relevant predictors, though physical understanding must be employed to determine if predictors are reasonable

Current Turbulence Prediction Methods and Limitations (2)

Supplementary Weather Product (AIM 7-1-3): Clear-air turbulence forecast only.
See FYI/Help page for more information.

GTG2 - Maximum turbulence intensity (10000 ft. MSL to FL450)

Valid 1800 UTC Mon 21 Jun 2010

00-hr forecast from 1800 UTC 21 Jun

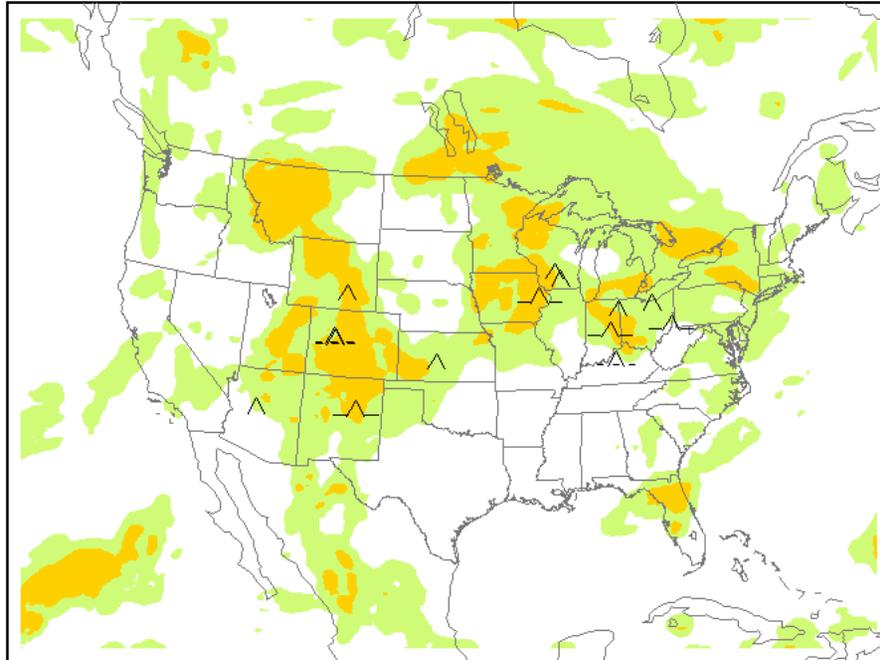


Image Courtesy: www.aviationweather.gov

Graphical Turbulence Guidance (GTG)

- Combination of turbulence diagnostic quantities derived from 3D forecast grids
- Limitations:
 - Grid is much too coarse in relation to aircraft size

Current Turbulence Prediction Methods and Limitations (3)

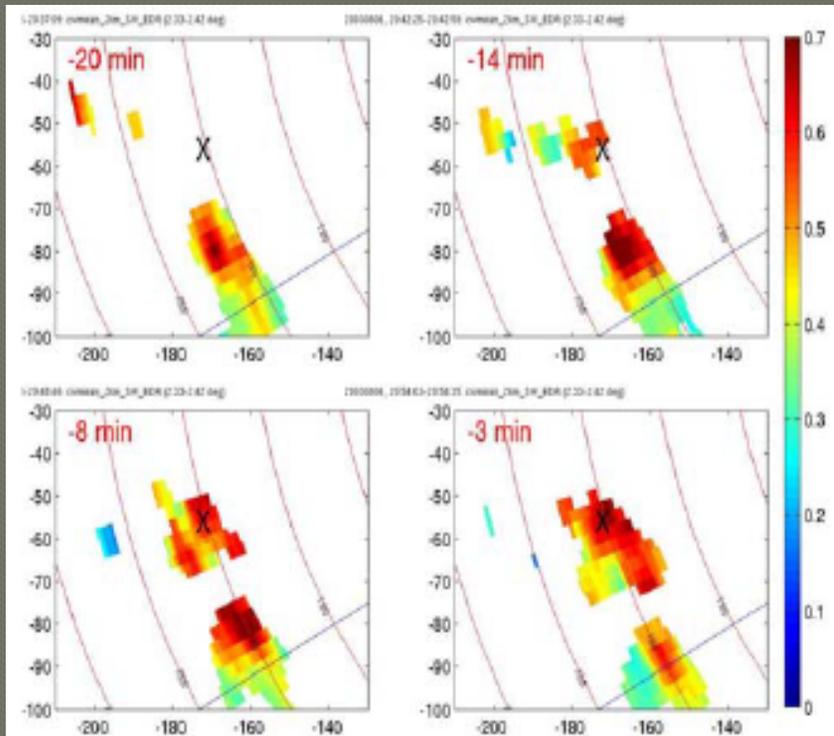


Figure 7: NTDA EDR from KPAH 2.4° sweeps at 20:37, 20:43, 20:49, and 20:54 UTC on August 6, 2003, ranging from 20 minutes to 3 minutes before the severe turbulence encounter described in the text. The EDR color scale ranges from 0 to 0.7 $m^{2/3}/s$.

- NCAR Turbulence Detection Algorithm (NTDA)
 - Utilizes NEXRAD radar reflectivity data to diagnose turbulent conditions
 - Very rapid update cycle
 - Limitations:
 - Only available in cloud, CIT missed

Image Courtesy: Williams et al. (2004)

Method

- Keep all data we care about

- Within 40 nautical miles
- Above 15,000 feet
- Decide on thresholds to distinguish objects

- Create objects

- Rain, convection, hail, lightning, vertically integrated liquid (VIL), clouds, aircraft, EDR

- Create relations

- SRRF's work SPATIALLY and TEMPORALLY

