Improved Convective Initiation Forecasting in the Gulf of Mexico Region through Enhanced uses of NASA Satellite Assets and Artificial Intelligence

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15th Conference on ARAM, Los Angeles, California

NASA Advance Satellite Aviation Weather Products Initiative
NASA ROSES 2007 & 2009
Collaborators: NASA SPoRT

Motivation: Operational weather prediction models are currently poor at pinpointing locations and timing of convective storm initiation within 0-6 hour timeframe. While extrapolation techniques work well for pre-existing storms, they do not apply to new storm formation.

The present study will fuse operational satellite and model data using artificial intelligence techniques to create improved CI forecasts over both land and water in the Gulf of Mexico.

Background & Goals

• MODIS datasets will be used to form *land surface heating gradient* and *land surface variability* (i.e. heterogeneity) which have been correlated with the formation of non-classical mesoscale circulations that support cumulus cloud development, and therefore help identify potential locations for thunderstorm formation within 1-6 hour timeframes.

• Artificial Intelligence techniques will be employed to identify new data for incorporation into the SATellite Convection AnalySis and Tracking (SATCAST) convective initiation algorithm, to optimize SATCAST and to create a probabilistic predictive model of early storm development, 0-1, 1-6 and 24 hours into the future.

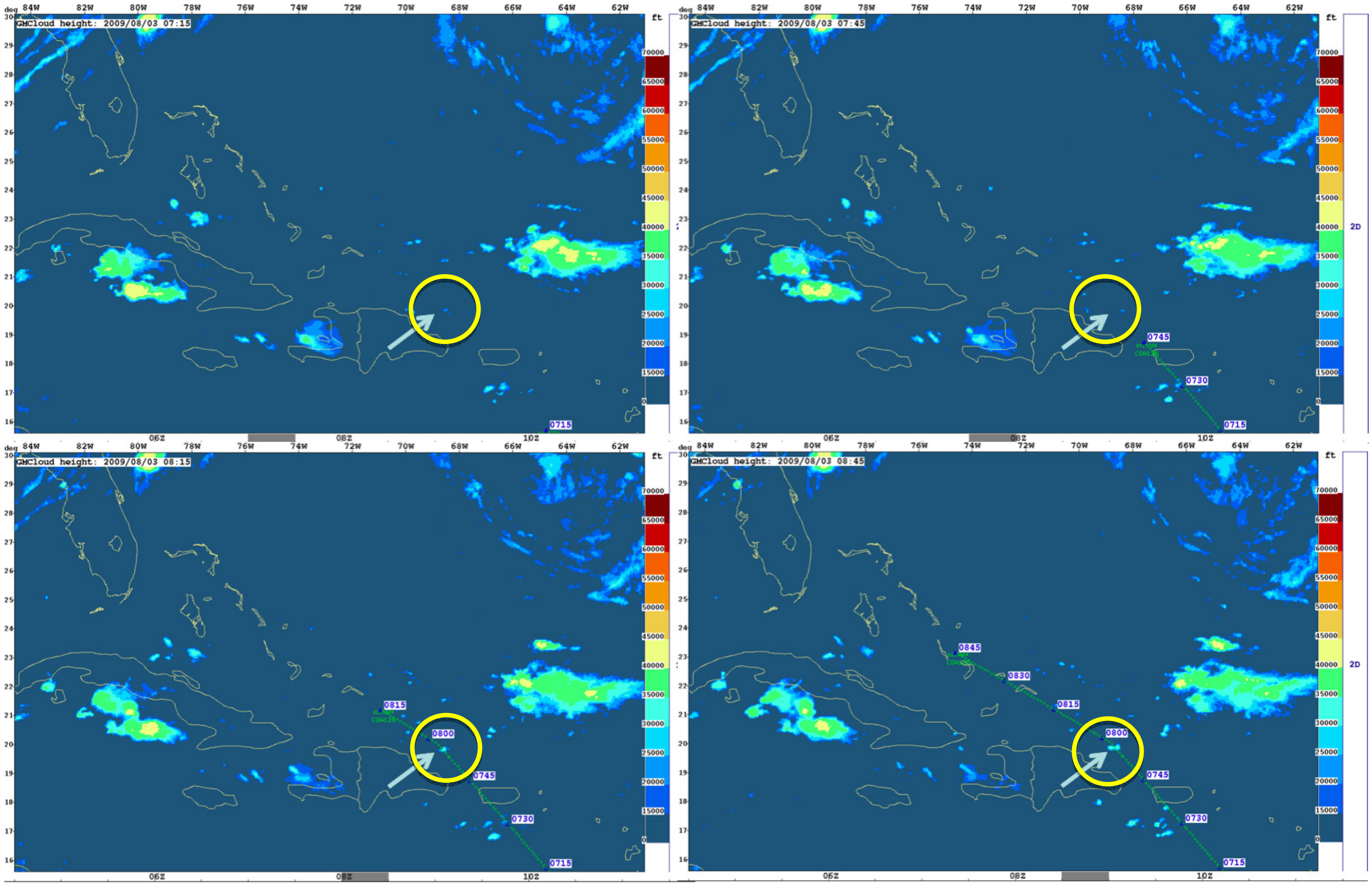
• Use of the Thunderstorm Artificial Neural Network (TANN) algorithm, including the NASA datasets, in addition to NASA Land Information System (LIS) fields and perhaps AMSR-E sea surface temperatures, will improve 1-6 hour thunderstorm forecasts in the vicinity of southern Texas.

• Emphasis is on enhancing convective nowcasting accuracy for Gulf of Mexico region airports.

• TRMM, CloudSat and GOES-based CI training database used to characterize storms to define "truth" for tuning and verification.

The “A-Train” data to be used is TRMM, AMSR-E, MODIS and CloudSat data, in combination with algorithms that rely on GOES, as well as the Artificial Intelligence forecast methods.

Cloud top heights derived from GOES-East via the NASA-funded Convective Diagnosis Oceanic product show the path of Continental Airlines 128 on August 3, 2009. The aircraft track is overlaid, and an arrow points to the location of the Boeing 767's <u>convectively induced turbulence encounter</u> above a rapidly-growing convective cell at approximately 0756 UTC. The images are from 0715 (upper left), 0745 (upper right), 0815 (lower left), and 0845 (lower right).



Example of SATCAST implementation in CoSPA Forecast

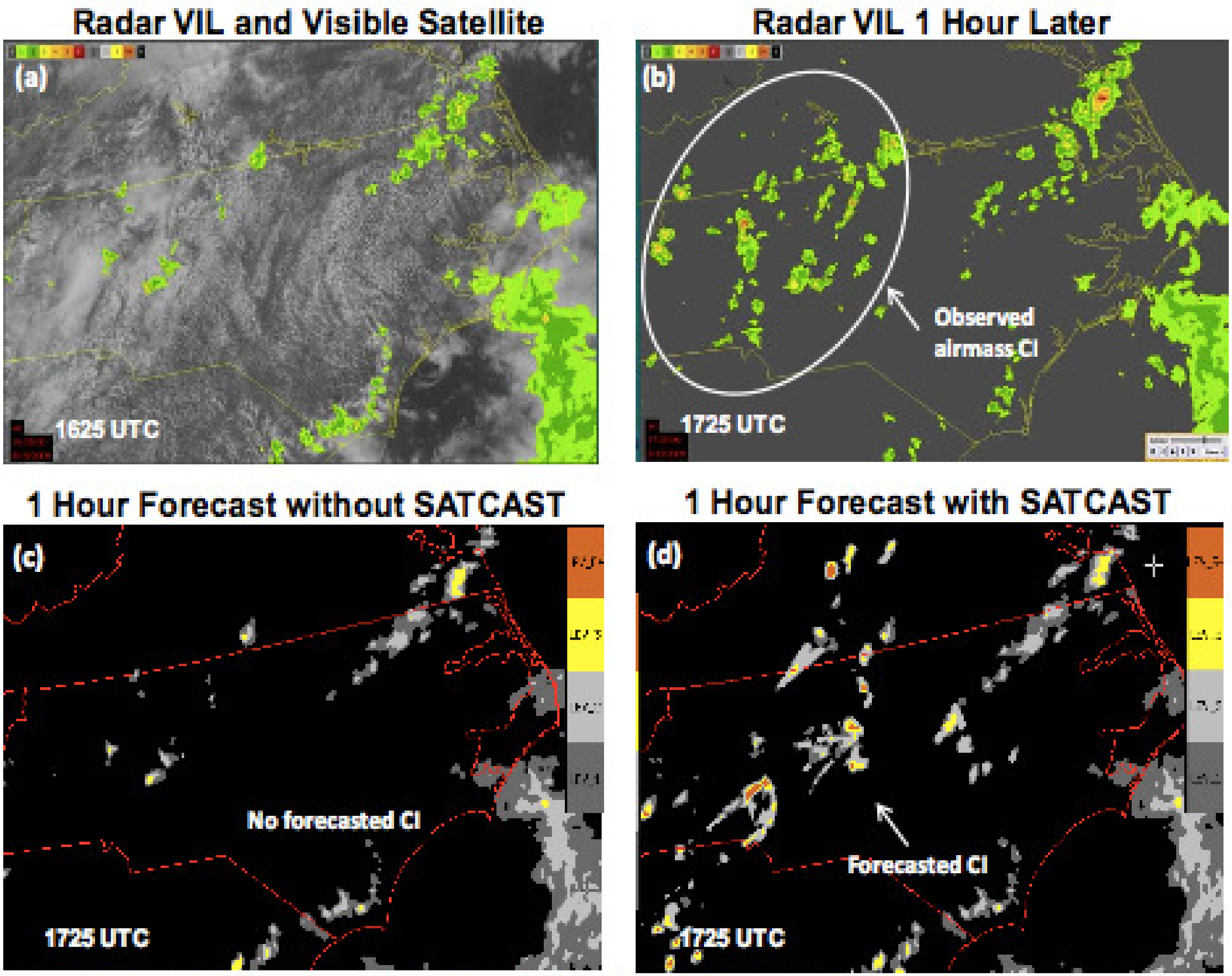


Figure 13. Example of airmass initiation using SATCAST in CoSPA. *a) Visible satellite and radar VIL over NC at 1625 UTC 15 May 2009 shows limited VIL in this region and little coherent structure in the cloud field. (b) The observed VIL 1 hour later shows that scattered, cellular airmass storms have initiated over NC. (c) The VIL forecast without SATCAST CI does not depict the newly-developed storms, whereas the forecast with the SATCAST CI (d) captures the convective initiation and the scattered nature of the convection.*

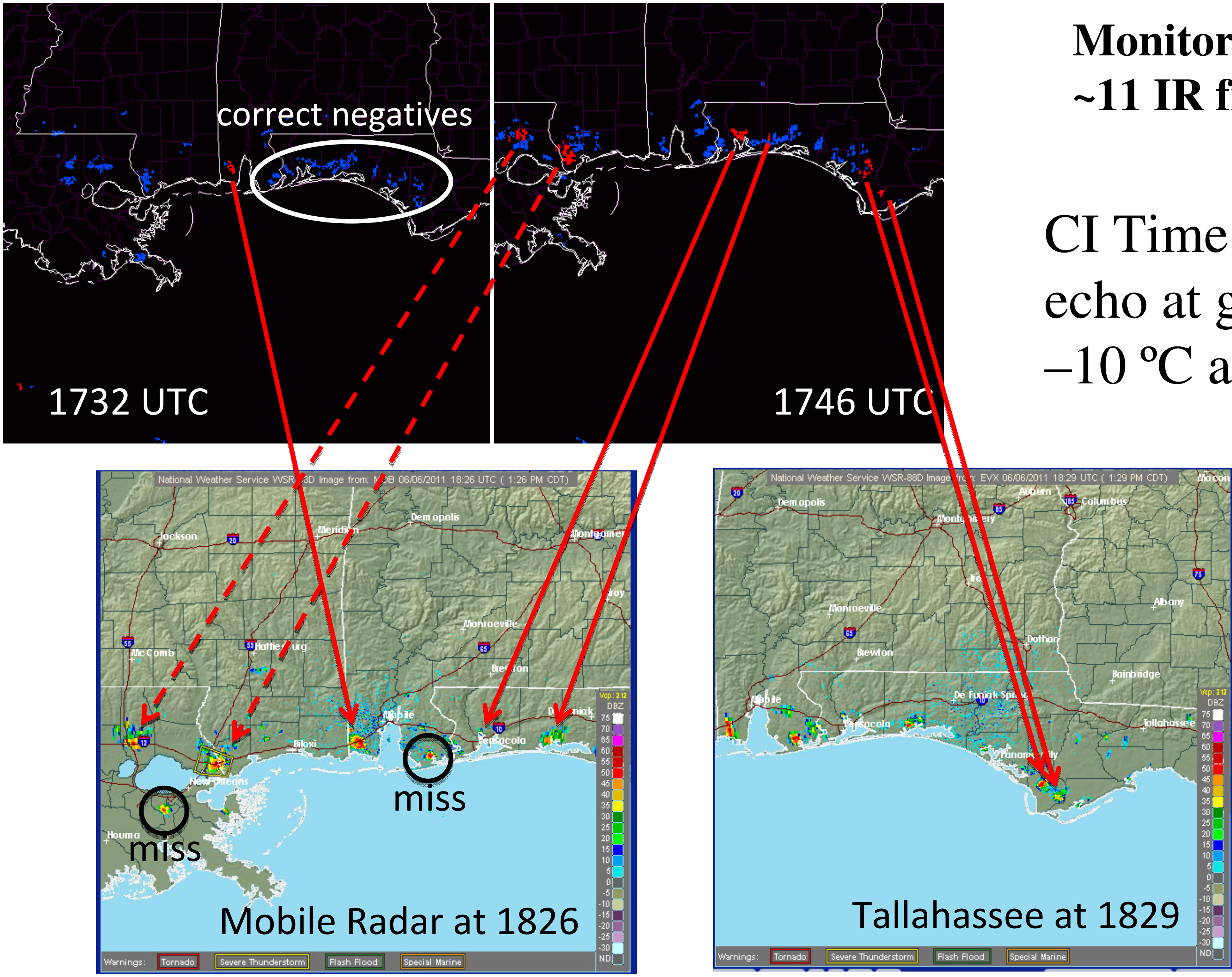
Outline

1. **Algorithms for 0-6 hour CI nowcasting**
   a) Random Forest methods, relevant to convective nowcasting
   b) The Artificial Neural Network (ANN) Thunderstorm forecasting model
   c) GOES 0-1 hour convective and lightning initiation nowcasting

2. **Enhancements to RF and TANN**
   a) Heating indices/NCMC and 1-6 hour thunderstorm forecasting
   b) Land Surface Variability fields
   c) Development of CI training database (contingency table)
   d) Leveraging ROSES 2007 results

Methods: Convective Nowcasts/Diagnoses

SATellite Convection AnalySis and Tracking (SATCAST) System



Monitor…
~11 IR fields for GOES:

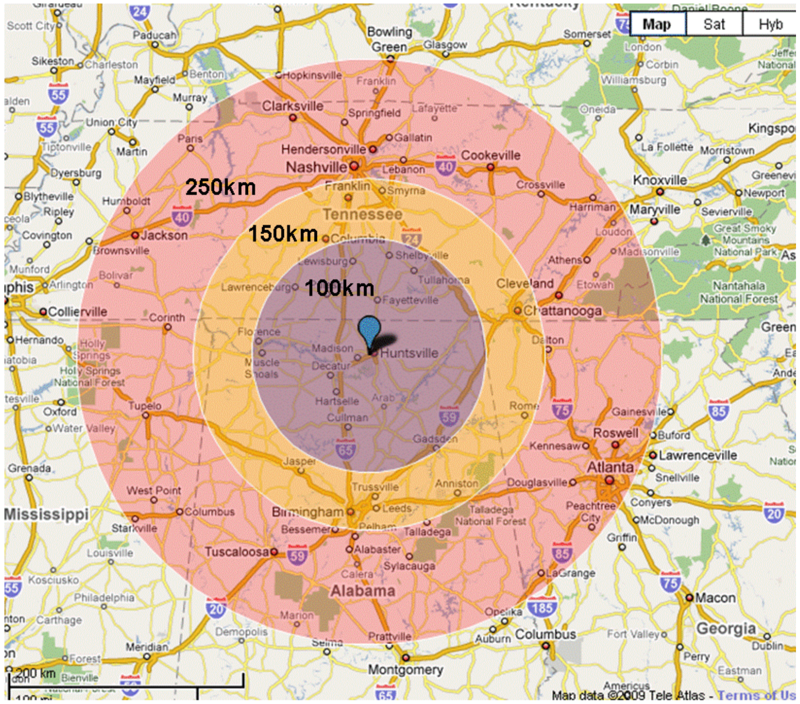
CI Time: 1st ≥35 dBZ echo at ground, or at –10 ºC altitude

Walker et al. (2011)

SATCAST Algorithm: *GOES IR Interest Fields*

CI Interest Field	Purpose and Resolution	Critical Value
6.5 – 10.7 μm difference **(IF1)**	4 km cloud-top height relative to upper-tropospheric WV weighting function (Schmetz et al. 1997)	–35° C to –10° C
13.3 – 10.7 μm difference **(IF2)**	Cloud-top height assessment (Inoue 1987a,b; Mecikalski and Bedka 2006)	–25° C to –5° C
10.7 μm T_B **(IF3)**	4 km cloud-top glaciation (Roberts and Rutledge 2003)	–20° C < T_B < 0° C
10.7 μm T_B Drop Below 0° C **(IF4)**	4 km cloud-top glaciation (Roberts and Rutledge 2003)	Within prior 30 mins
10.7 μm T_B Time Trend **(IF5, IF6)**	4 km cloud-top growth rate/updraft strength (Roberts and Rutledge 2003)	< –4° C/15 mins ΔT_B/30 mins < ΔT_B/15 mins
6.5 – 10.7 μm Time Trend **(IF7)**	4 km multi-spectral cloud growth (Mecikalski and Bedka 2006)	> 3° C/15 mins
13.3 – 10.7 μm Time Trend **(IF8)**	8 km multi-spectral cloud growth (Mecikalski and Bedka 2006; Mecikalski et al. 2008)	> 3° C/15 mins
3.9 μm Fractional Reflectance **(IF9)**	4 km cloud-top glaciation (Lindsey et al. 2006, 2010; Lindsey and Grasso 2008)	≤ 5%
3.9 – 10.7 μm Time Trend **(IF10)**	4 km cloud-top glaciation (Siewert 2008; Harris et al. 2010)	$t - (t_{-1}) \leq -5$ K and $t - (t_{+1}) \leq -5$ K
15-/30-min Trend in 3.9 μm Fraction Reflectance **(IF11)**	4 km cloud-top glaciation (Siewert 2008; Harris et al. 2010)	Continually decreasing below 10%

SATCAST Algorithm: *Lightning Initiation Interest Fields*



- NASA North Alabama total-cloud, Lightning Mapping Array network, used to identify first flash(<u>above</u>)
- All 10 lightning initiation interest fields as available from current GOES-12 imagery (<u>right</u>)

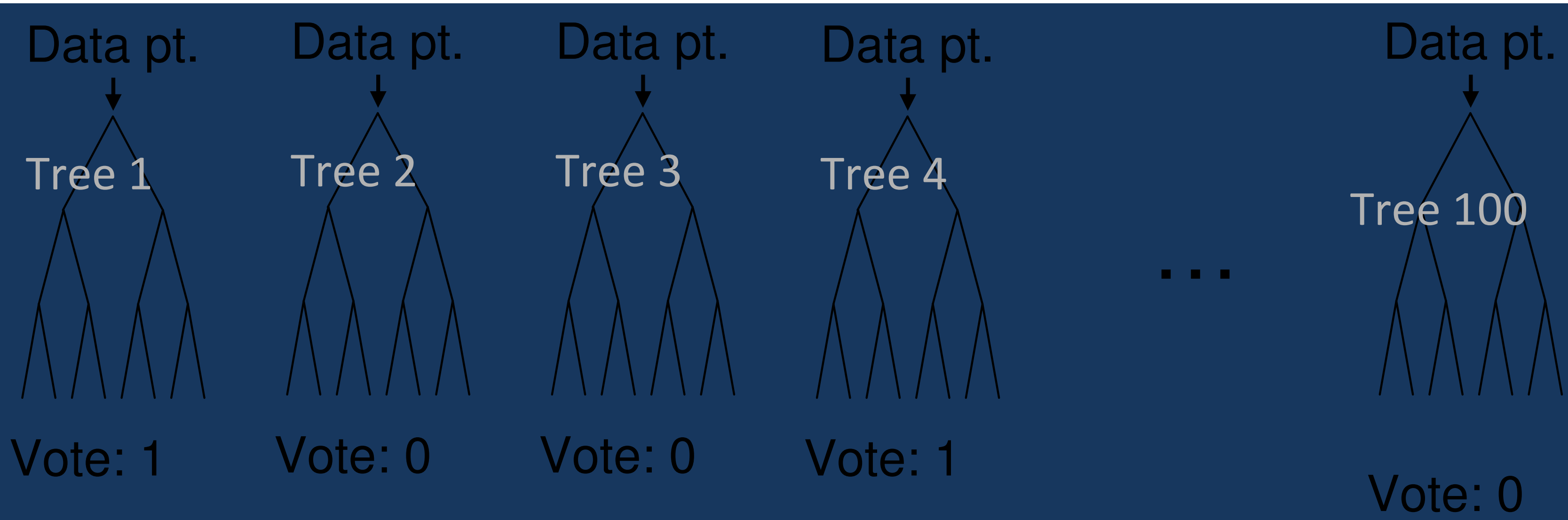
Harris, R. J., J. R. Mecikalski, W. M. MacKenzie, Jr., P. A. Durkee, and K. E. Nielsen, 2010: Definition of GOES infrared fields of interest associated with lightning initiation. *J. Appl. Meteor. Climatol*. **49**, 2527-2543.

Interest Field	MB06 Critical CI Value	Siewert LI Value	15 to 30-min Threshold (This LI Study)	Description
10.7 μm T_B	< 0°C	≤ −13°C	*< 0° C*	Cloud tops cold enough to support supercooled water and ice mass growth; cloud−top glaciation
10.7 μm T_B Time Trends[1]	< −4°C / 15 min (ΔTb / 30 min < ΔTb / 15 min)	≤ −10°C / 15 min	*< −6° C / 15 min*	Cloud growth rate (vertical)
Timing of 10.7 μm T_B drop below 0° C	Within prior 30 min	*Not used*	*Not Used*	Cloud−top glaciation
6.5−10.7 μm T_B difference	Tb Diff: −35°C to −10°C	≥ −17°C	*> −30° C*	Cloud top height relative to mid/upper troposphere
13.3−10.7 μm T_B difference	Tb Diff: −25°C to −5°C	≥ −7°C	*> −13° C*	Cloud top height relative to mid/upper troposphere; better indicator of early cumulus development but sensitive to cirrus
6.5−10.7 μm T_B Time Trend	> 3°C / 15 min	≥ 5°C / 15 min	*> 5° C / 15 min*	Cloud growth rate (vertical) toward dry air aloft
13.3−10.7 μm T_B Time Trend	> 3°C / 15 min	≥ 5°C / 15 min	*> 4° C / 15 min*	Cloud growth rate (vertical) toward dry air aloft
3.9−10.7 μm T_B Difference[3]	*Not used*	*Not used*	*> 17° C*	Cloud−top glaciation
3.9−10.7 μm T_B Time Trend[2]	*Not used*	T−T(t−1) < −5°C and T−T(t+1) < −5°C	*> 1.5° C / 15 min*	Sharp decrease, then increase indicates cloud−top glaciation
3.9 μm Fraction Reflectance[2]	*Not used*	≤ 0.05	*< 0.11*	Cloud top consists of ice (ice is poorer reflector than water at 3.9 μm)
3.9 μm Fraction Reflectance Trend[3]	*Not used*	*Not used*	*< −0.02 / 15 min*	Cloud−top glaciation rate

1 Represents two unique 10.7 μm T_B interest fields in MB06. No 30-min trends were used in Siewert (2008) or in this study.
2 Added to MB06 fields by Siewert (2008).
3 Unique to this study.

Random Forest (RF) Data Mining

- RF is a non-linear data mining technique used to analyze a retrospective database and…
  - Produce estimates of variable importance
  - Create a non-parametric (no assumptions about functional form), probabilistic empirical predictive model via an ensemble of decision trees (*all combinations of all variables*)
  - Identify the most valuable SATCAST components and additional variables for convective initiation prediction
- Method can be used for any problem where a potential predictor values are paired with a binary (yes/no) predictand

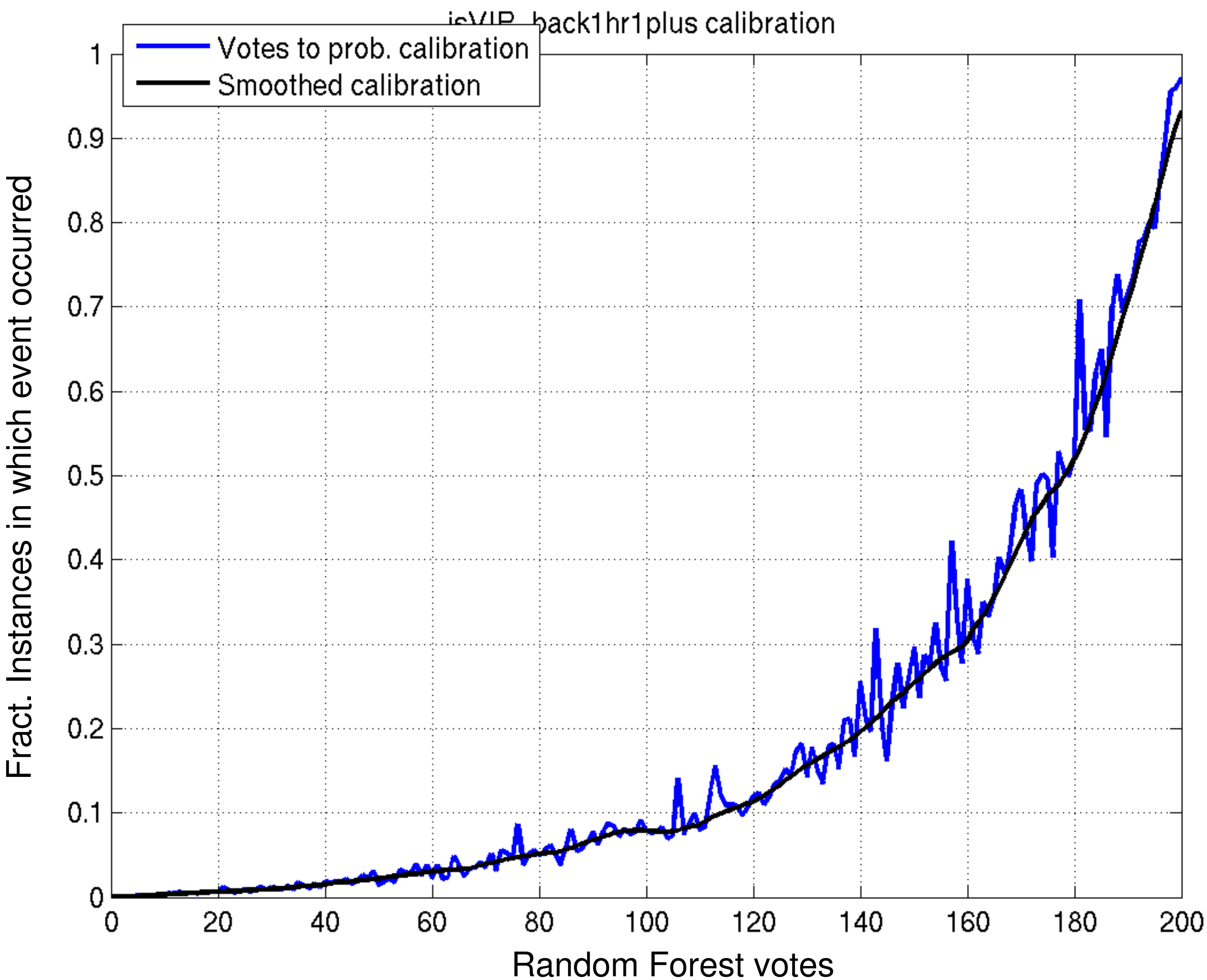


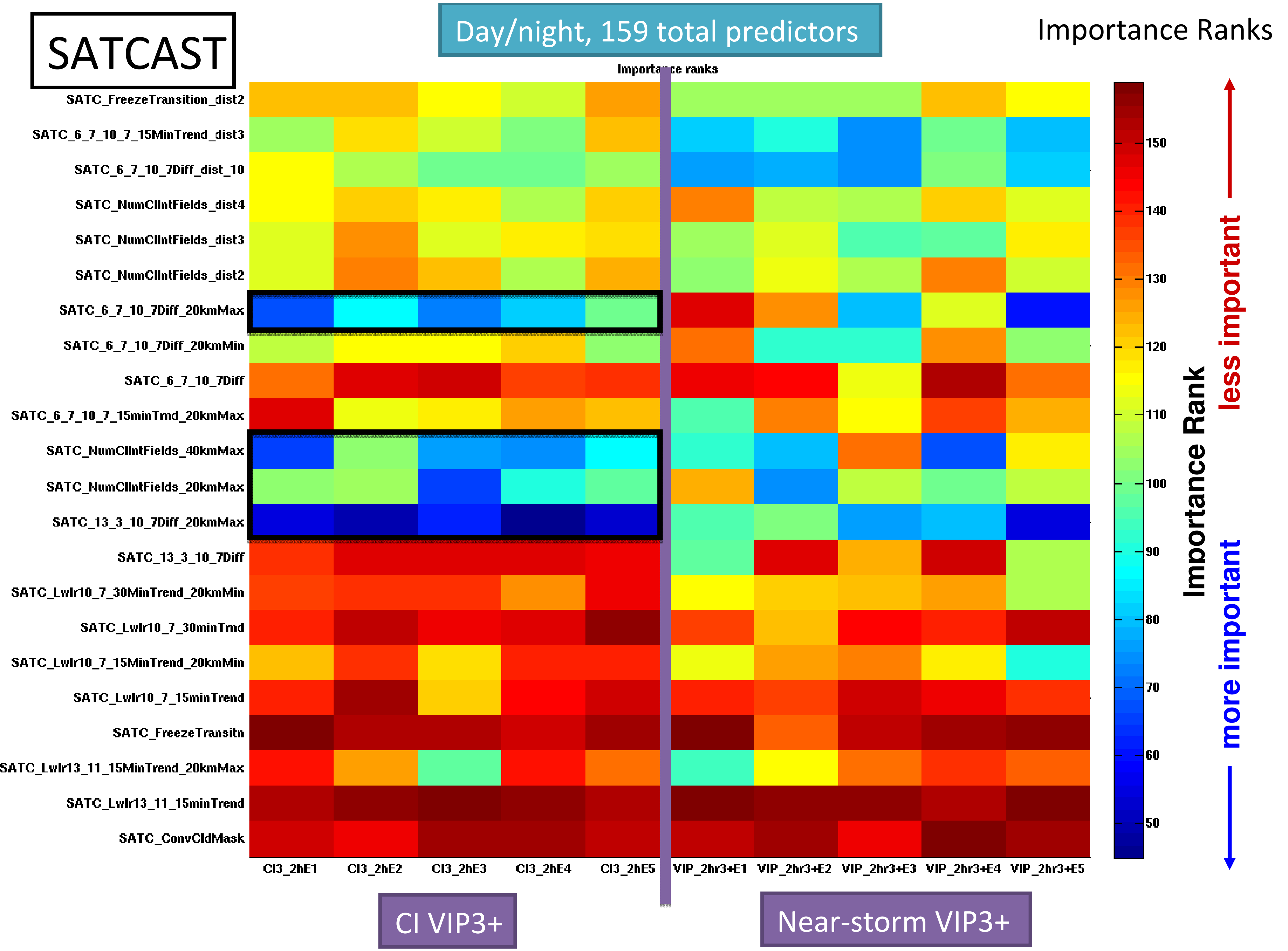
=> 40 votes for "0", 60 votes for "1" can be translated into a probability

RF Methodology

- Define VIP1 initiation as the observation of VIP1+ at least 40 km away from where any VIP1+ was at the analysis time, adjusted for storm motion
  - VIP 1+ is equivalent to VIL > 0.14 kg m^{-2}
- Define VIP3 initiation as the observation of VIP3+ at least 40 km away from where any VIP3+ was at the analysis time, adjusted for storm motion
  - VIP 3+ is equivalent to VIL > 3.5 kg m^{-2}
- Associating potential predictor variables with initiation "truth" at each pixel (adjusted for storm motion) permits statistical analysis of variable significance and construction of a predictive model
- For each problem, randomly resample sets of "true" and "false" pixels from dataset (sample more of rare event)
- Even Julian days used for training, odd for testing and vice-versa
  - Multiple training/testing subsets used for cross-validation

Example RF probability calibration
1-hr, VIP 1+ prediction

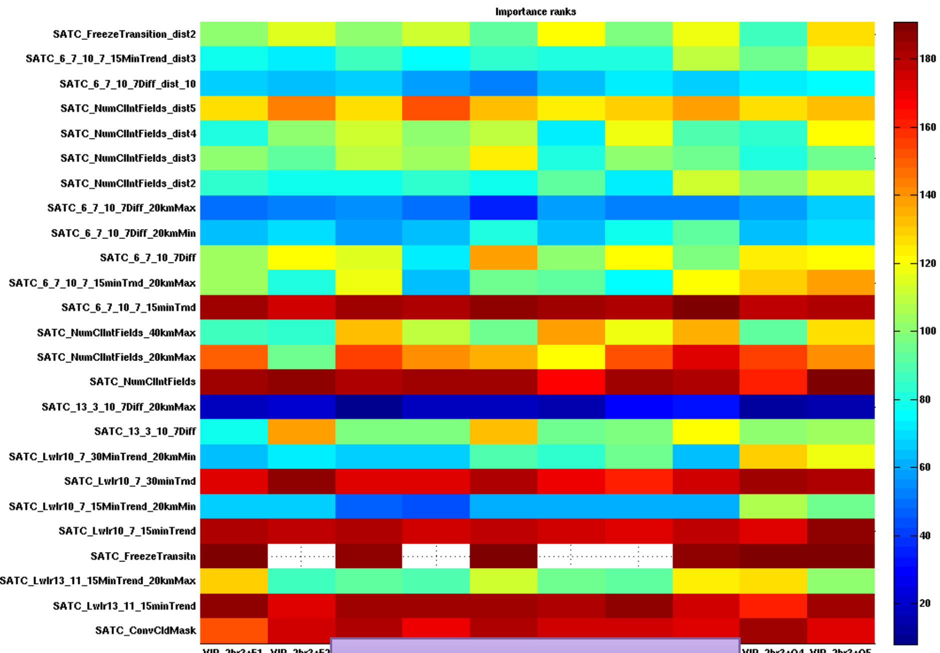



SATCAST
Day/night, 159 total predictors
Importance Ranks
Importance ranks
SATC_FreezeTransition_dist2
SATC_6_7_10_7_15MinTrend_dist3
SATC_6_7_10_7Diff_dist_10
SATC_NumClIntFields_dist4
SATC_NumClIntFields_dist3
SATC_NumClIntFields_dist2
SATC_6_7_10_7Diff_20kmMax
SATC_6_7_10_7Diff_20kmMin
SATC_6_7_10_7Diff
SATC_6_7_10_7_15minTrnd_20kmMax
SATC_NumClIntFields_40kmMax
SATC_NumClIntFields_20kmMax
SATC_13_3_10_7Diff_20kmMax
SATC_13_3_10_7Diff
SATC_Lwlr10_7_30MinTrend_20kmMin
SATC_Lwlr10_7_30minTrnd
SATC_Lwlr10_7_15MinTrend_20kmMin
SATC_Lwlr10_7_15minTrend
SATC_FreezeTransitn
SATC_Lwlr13_11_15MinTrend_20kmMax
SATC_Lwlr13_11_15minTrend
SATC_ConvCldMask
CI3_2hE1
CI3_2hE2
CI3_2hE3
CI3_2hE4
CI3_2hE5
VIP_2hr3+E1
VIP_2hr3+E2
VIP_2hr3+E3
VIP_2hr3+E4
VIP_2hr3+E5
CI VIP3+
Near-storm VIP3+
150
140
130
120
110
100
90
80
70
60
50
Importance Rank
less important
more important

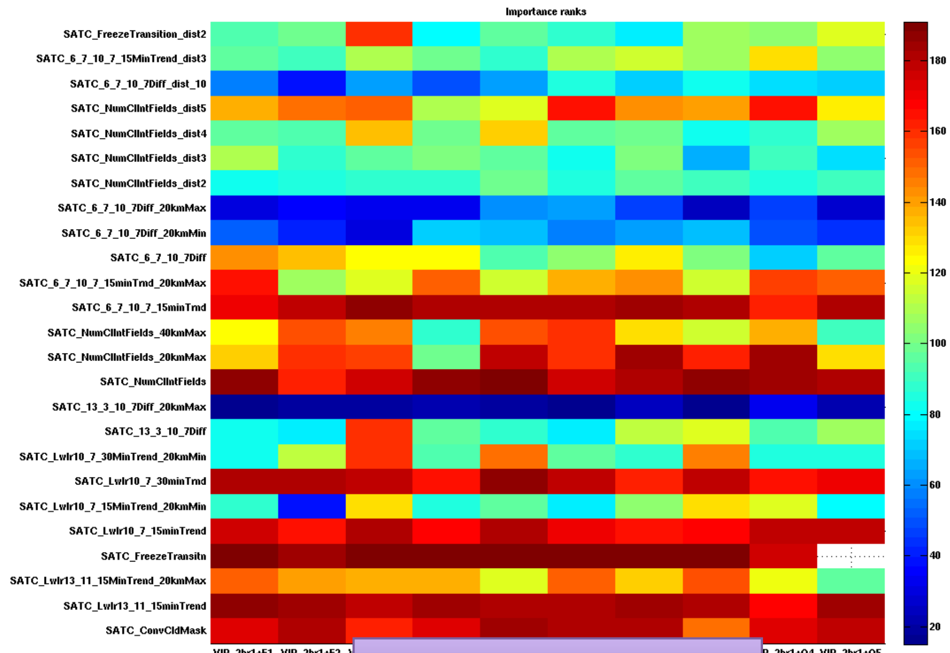
SATCAST

Daytime only , 191 total predictors

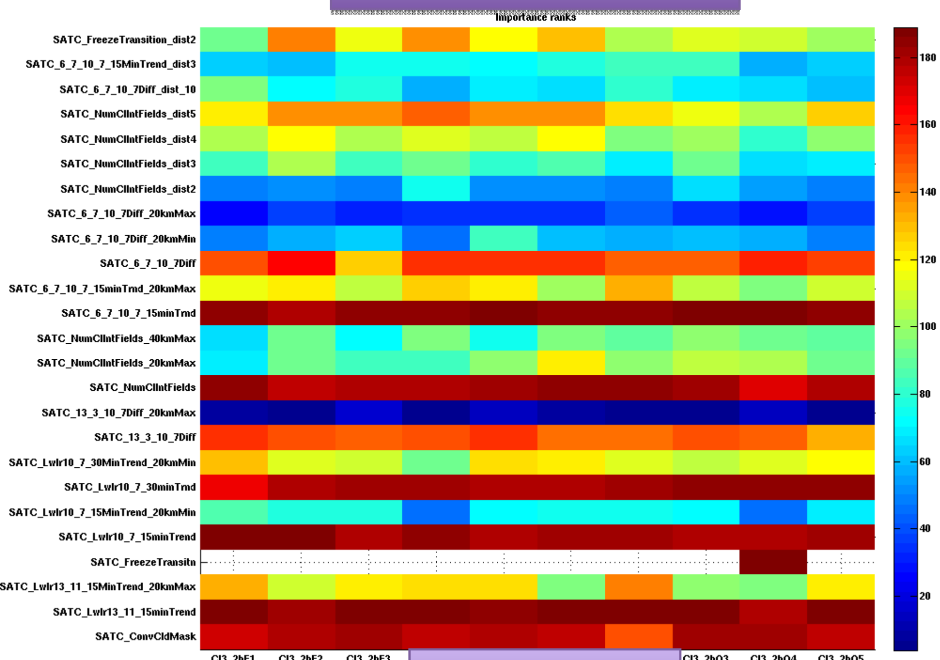
Importance Ranks



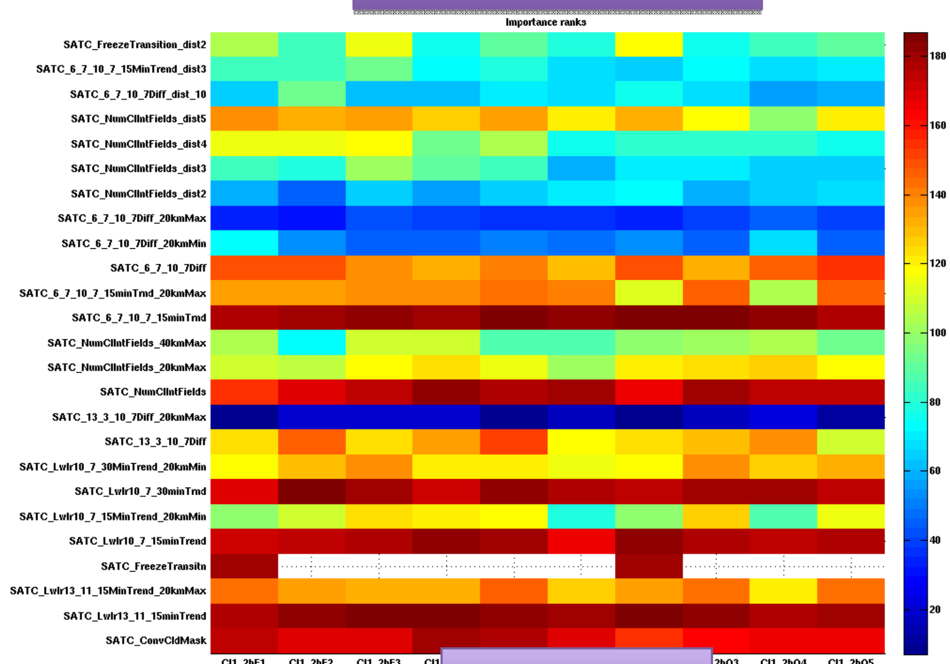
Near-storm regime VIP3+



Near-storm regime VIP1+



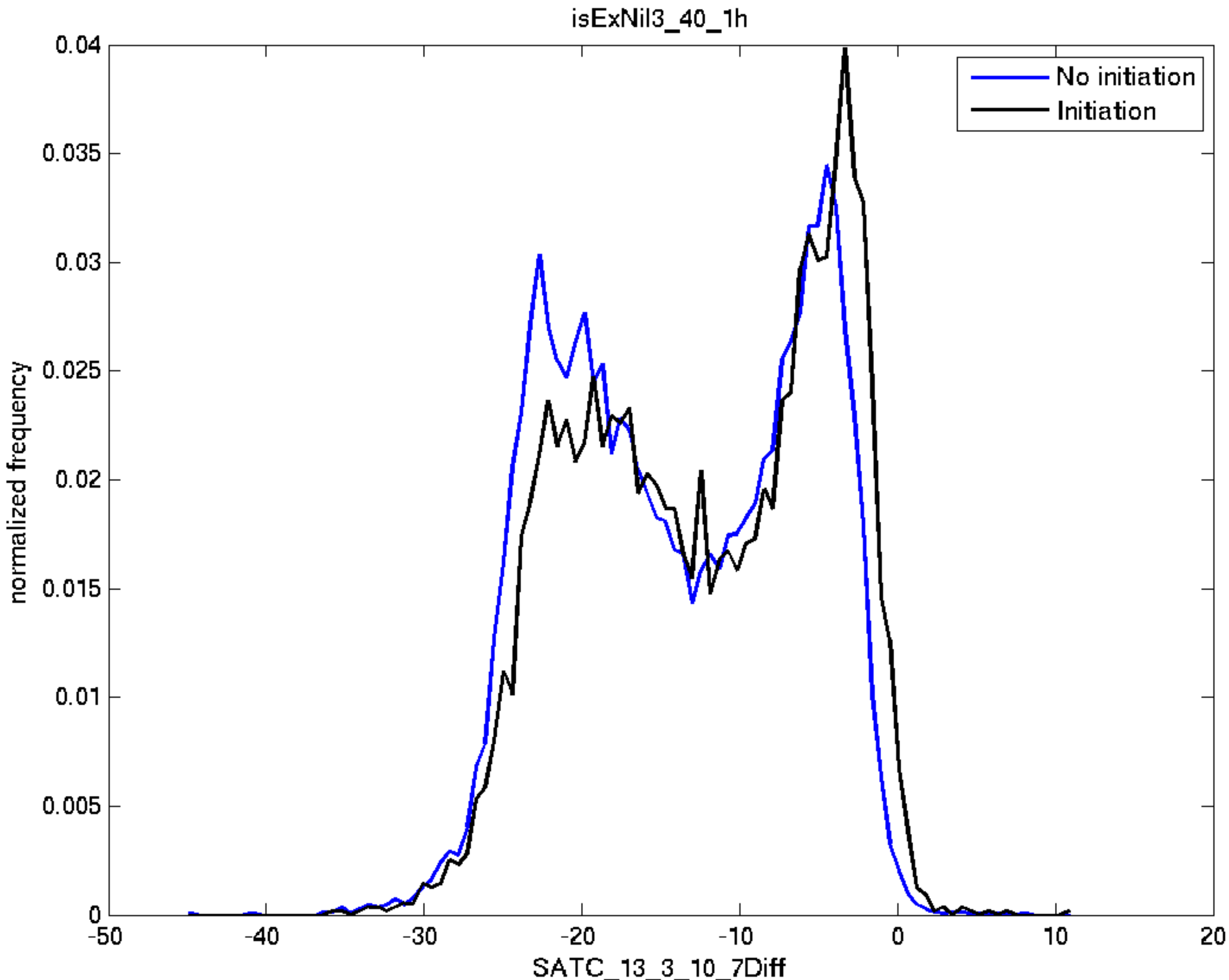
CI regime VIP3+



CI regime VIP1+

Conditional histograms

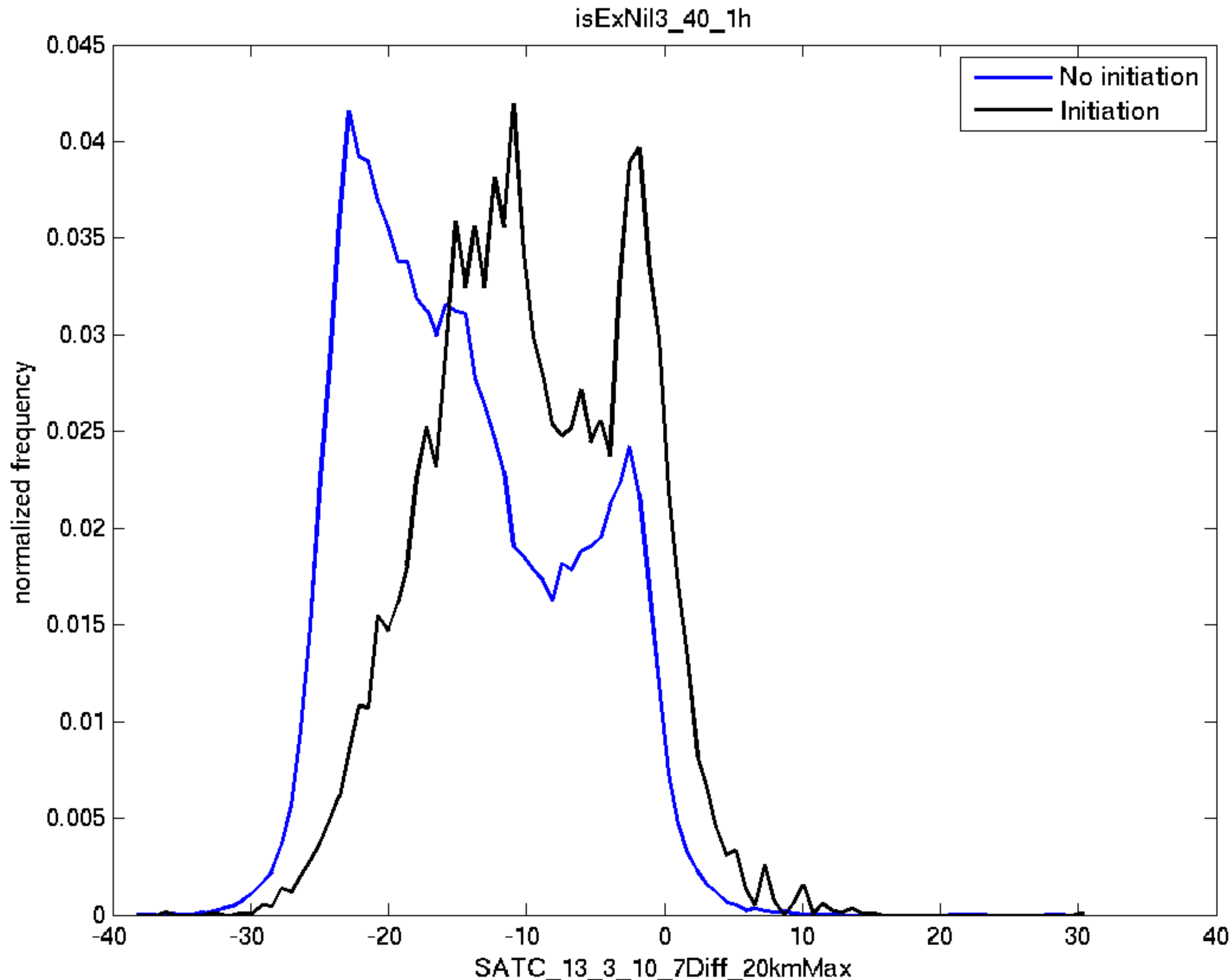
13.3-10.7 micron, 1-hr, 40 km VIP 3+ initiation



- Note: very little discrimination capability

Conditional histograms

13.3-10.7 micron 20 km Max, 1-hr, 40 km VIP 3+ initiation



- Note: discrimination capability improved

RF Evaluation on 2009 data

CI regime: VIP Level 3+ (daytime only)

	Max CSI	Max TSS	AUC
2h simple extrapolation	0.005 ± 0.002	0.17 ± 0.05	0.60 ± 0.03
CoSPA (2h)	0.012 ± 0.005	0.12 ± 0.03	0.56 ± 0.02
LAMP 1-3h (2hr)	0.023 ± 0.006	0.56 ± 0.03	0.83 ± 0.01
2h RF	**0.032** ± 0.011	**0.68** ± 0.02	**0.91** ± 0.01

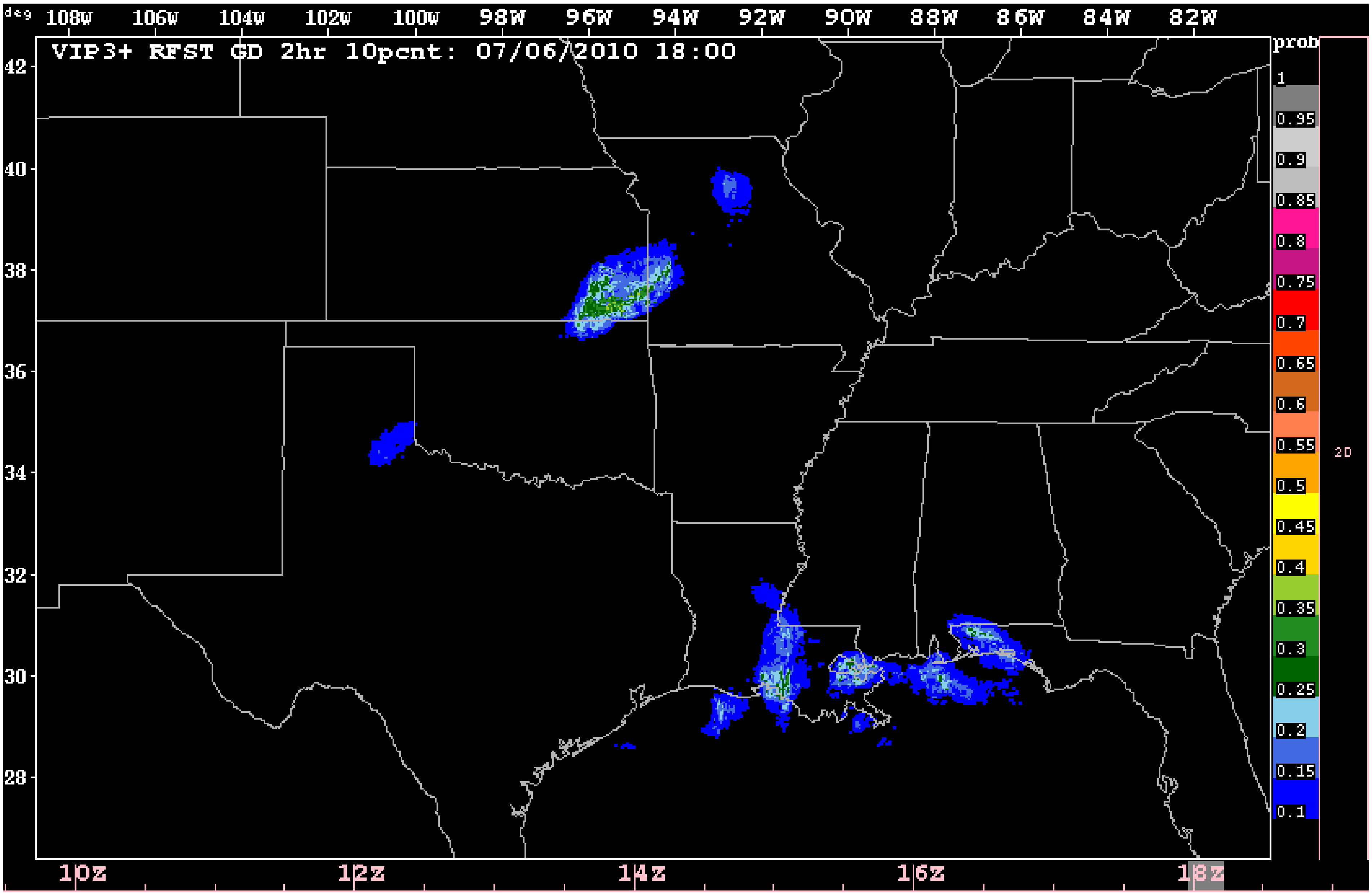
CSI = Critical Success Index

TSS = True Skill Score

AUC = Area Under the Receiver Operating Characteristic Curve

Example: RF probabilistic nowcast

VIP 3+, 2 hr forecast; only probabilities > 10% shown



ANN Thunderstorm Model

ANN Model to forecast thunderstorm activity up to 24 hours in advance, and with a spatial accuracy of 20-km in South Texas

ANN inputs include outputs from

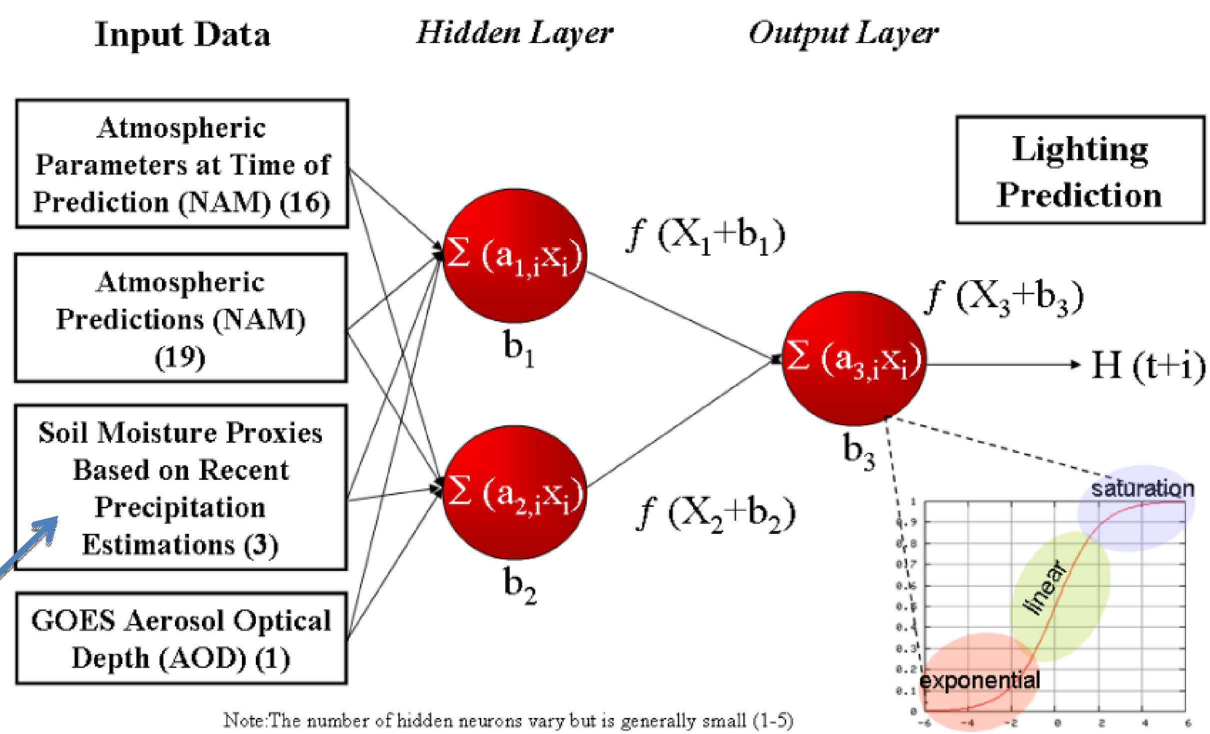
(1) deterministic mesoscale Numerical Weather Prediction (NWP) models,

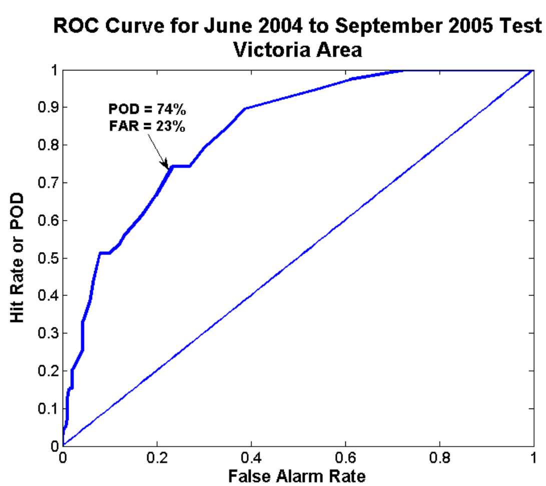
(2) selected sub-grid scale data that contributes to convective initiation, or CI.

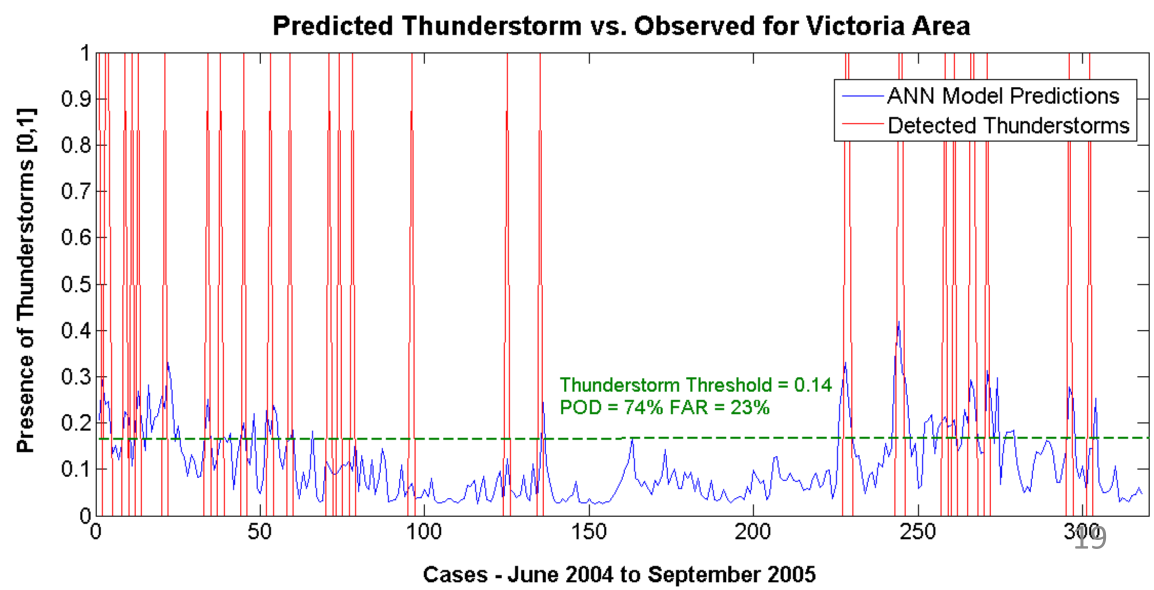
Waylon Collins, Corpus Christi Weather Forecast Office

Philippe Tissot, Texas A&M University-Corpus Christi

MODIS

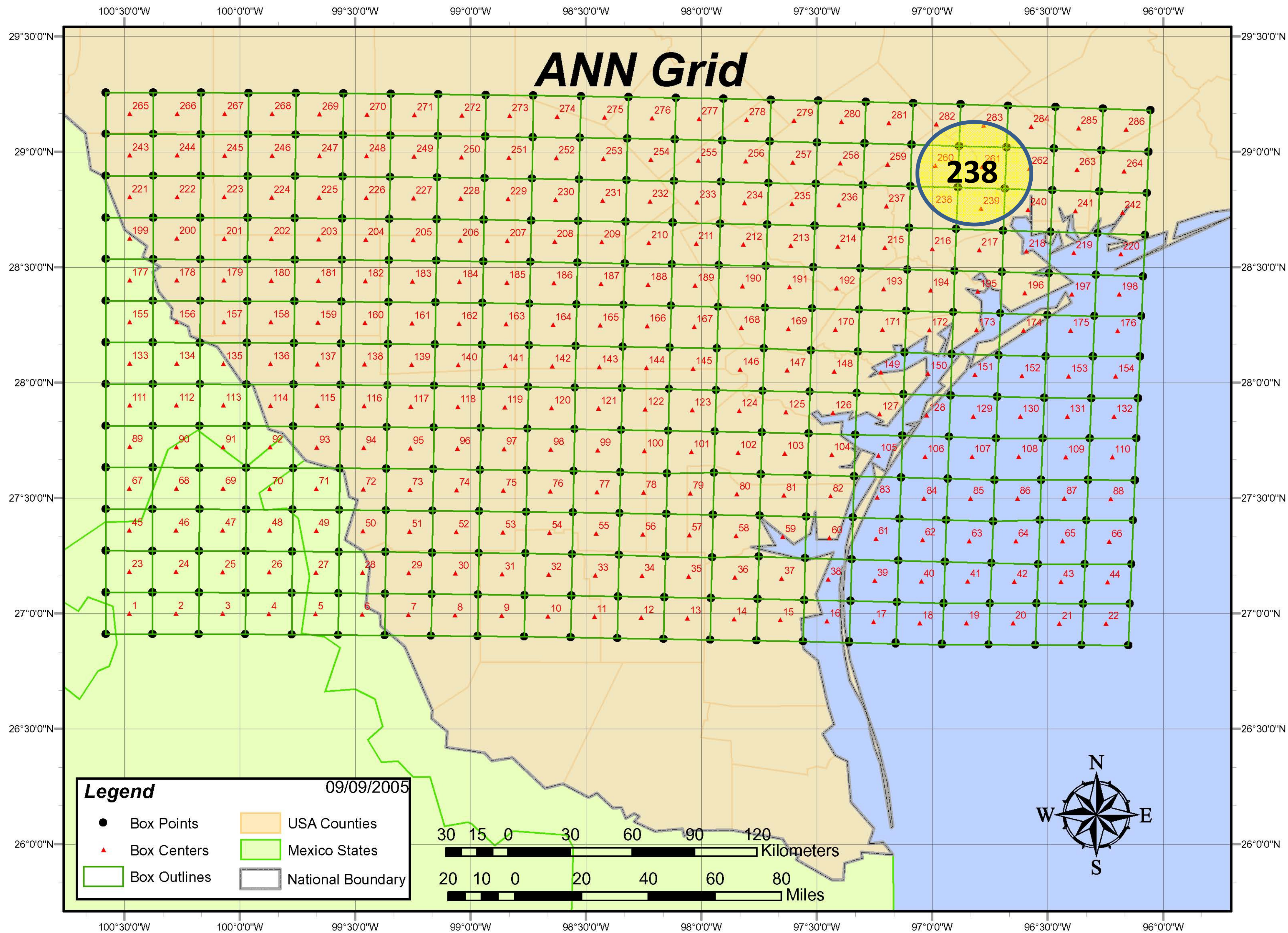






Victoria 07-08 Test Case (Box 238) TANN Input Variables

- 1: Date Values (yearly trig curve)
- 2-17: F00 NAM Current Atm State
  - 2-u_sfc[m/s],3-v_sfc,4-u_900,5-v_900,6-u_800,7-v_800,8-u_700,9-v_700,10-u_600,11-v_600,12-u_500,13-v_500,14-shear sfc-700 [x10-3 s-1],15-shear 900-700, 16-HI_Low [C],17-CTP_proxy[dimensionless]
- 18-36: F03F18 NAM Predictions:
  - 18-cp[kg/m^2],19-vv_925[Pa/s],20-vv_700,21-vv_500,22-u_sfc[m/s],23-v_sfc,24-u_850,25-v_850,26-s-8 shear[x10-3 s-1],27-8-6 shear[x10-3 s-1],28-t_sfc[K],29-pw[kg/m^2],30-li[K],31-cape[J/kg], 32-cin,33-dropoff[K],34-rh_850[%],35-mr_850[g/kg],36-LCL[m]
- 37: AOD
- 38: Ndry (number of previous dry days over the past 10 days)
- 39: MaxGradientAPI
- 40: Mean API
- 41: Max API
- 42: MeanBoxAPIGradient
- 43: Centroid Distance
- 44: Entropy
- 45: Purity
- 46: Random parameter (for RF – no impact on ANN)


ANN Grid
238
Legend
09/09/2005
Box Points
Box Centers
Box Outlines
USA Counties
Mexico States
National Boundary
30 15 0 30 60 90 120
Kilometers
20 10 0 20 40 60 80
Miles
N
S
E
W
100°30'0"W
100°0'0"W
99°30'0"W
99°0'0"W
98°30'0"W
98°0'0"W
97°30'0"W
97°0'0"W
96°30'0"W
96°0'0"W
29°30'0"N
29°0'0"N
28°30'0"N
28°0'0"N
27°30'0"N
27°0'0"N
26°30'0"N
26°0'0"N

Background text regarding model set-up

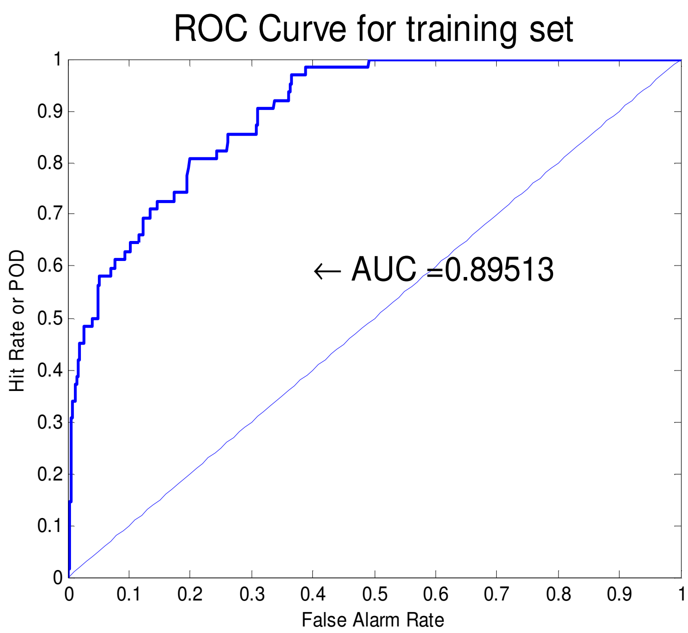
- The full data set (March 2004-December 2010) was used to determine a good artificial neural network architecture. Feedforward network with two hidden layers were tested. The data set was randomly divided into a training set (60%), a testing set (30%) and a validation set (10%). To prevent overfitting two strategies were compared, the use of a validation set with the levenberg-Marquardt training algorithm and the use of the Bayesian regularization algorithm, both as implemented in the Matlab Neural Network toolbox. In the case of the Bayesian regularization training, the validation set is automatically integrated with the training set. For both strategies a logsig function was used in the hidden layer while the number of hidden neurons and the function of the output neuron were varied. Overfitting was found to be a problem for all networks when a logsig function as used in the output neuron and for ANNs with 3 or more hidden neurons when using a logsig-purelin set of functions. The neural network architectures were compared by computing ROC curves

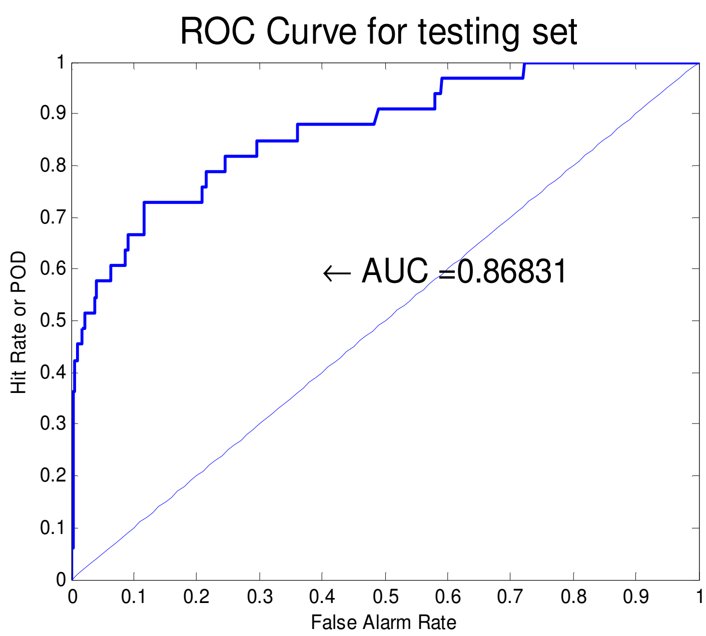
Background text regarding model set-up

- Best performance and stability and the smallest difference between training and testing set performance was obtained for a [1,1] ANN with logsig and purelin functions. This configuration was then used for a comparison between the TANN and the performance of the forecasters of the Corpus Christi Weather Forecast Office. Performance for the forecasters was recorded for the period of January 2007 to December 2008. The rest of the data set (March 2004 to December 2006 and January 2009 to December 2010) was divided into a training (70%) and testing set (30%). Based on the performance on the testing set and particularly the POD versus False Alarm Rate performance a threshold was selected. Lightnings during the 2007-2008 period were then predicted with the ANN and threshold selected on the rest of the data set.
- Data not available yet for forecasters

TANN Performance

- Example of Model calibration for a [1,1] ANN with logsig-logisg functions and all possible inputs. The data set was divided 60% training – 35% testing – 5% left for validation purposes.



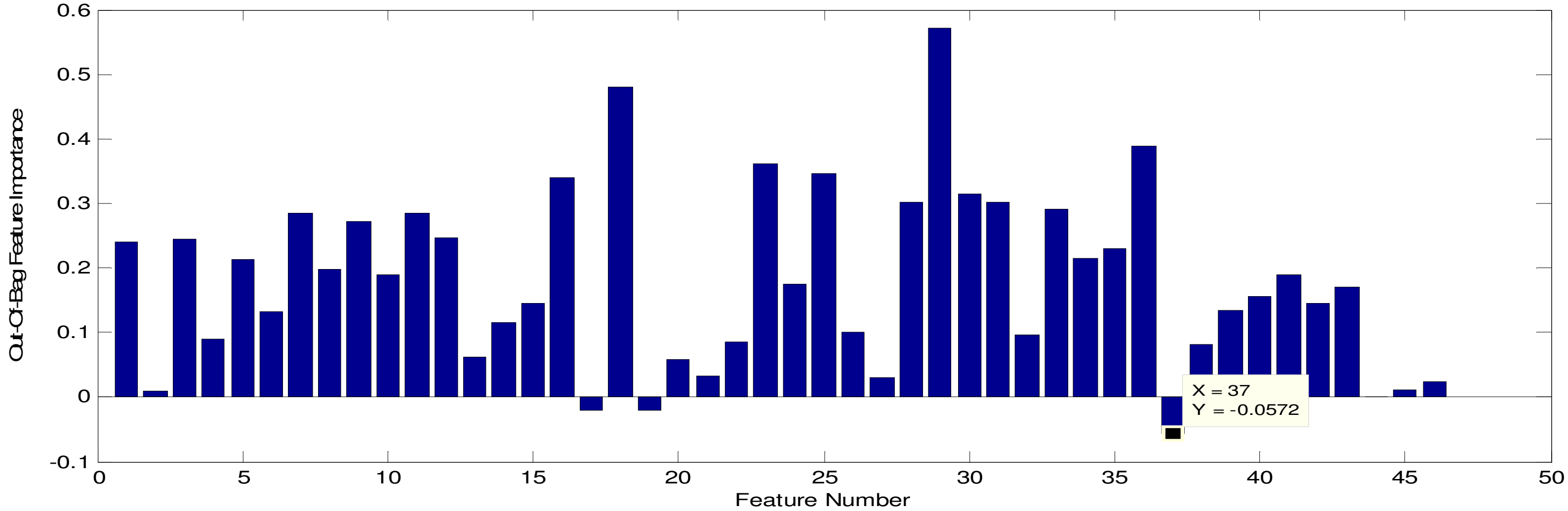


TANN Model Performance

- Model calibrated over March 2004 through December 2010 without the period 2007-2008 used for performance assessment (below)

	POD	F	CSI	Heidke	Peirce	YuleQ	CSS
3 hrs	0.93	0.22	0.12	0.17	0.71	0.96	0.12
6 hrs	0.97	0.33	0.19	0.22	0.64	0.97	0.19
9 hrs	0.81	0.25	0.21	0.25	0.56	0.85	0.20
12 hrs	0.78	0.22	0.08	0.10	0.55	0.85	0.07

Variable Importance from RF Modeling with same data set



- In the present model configuration the most important variable for thunderstorm predictions are 18-cp[kg/m^2], 29-pw[kg/m^2], and 36-LCL[m] (i.e. importance of NAM predictions with TANN ~ MOS) but many other variables contribute to model performance including subgrid scale inputs

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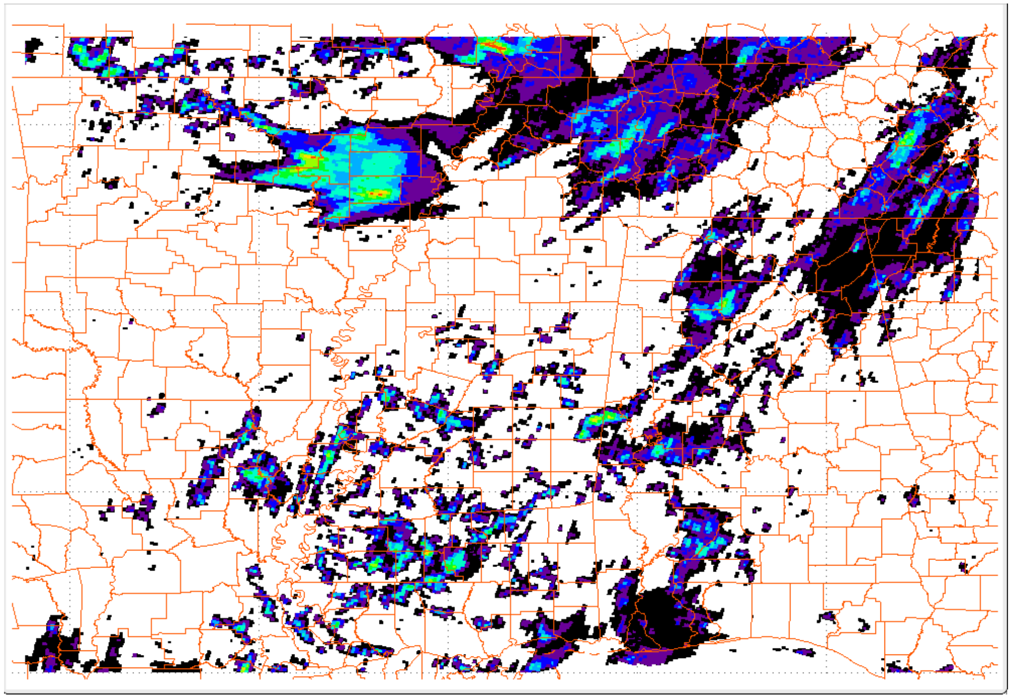
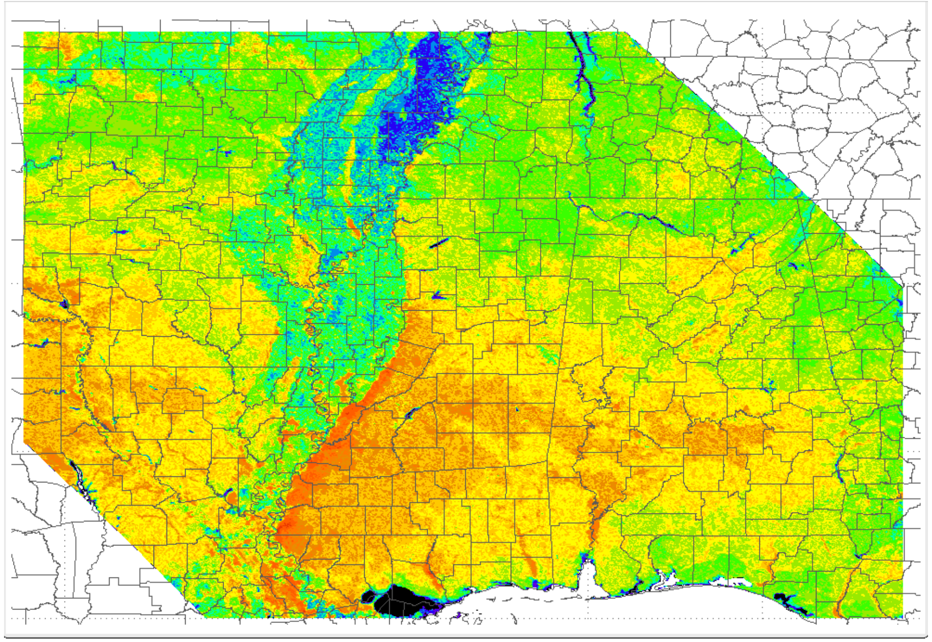
1-6 h CI Nowcasting:
Land-surface Heating Partitioning, Soil Moisture, Antecedent Rain

Goal: To demonstrate if one can predict today's convective initiation based on knowledge of "background" information, from the land surface (and the resultant heterogeneity in latent and sensible heating rates) and from antecedent precipitation.

→ **1-6 hour CI Index**

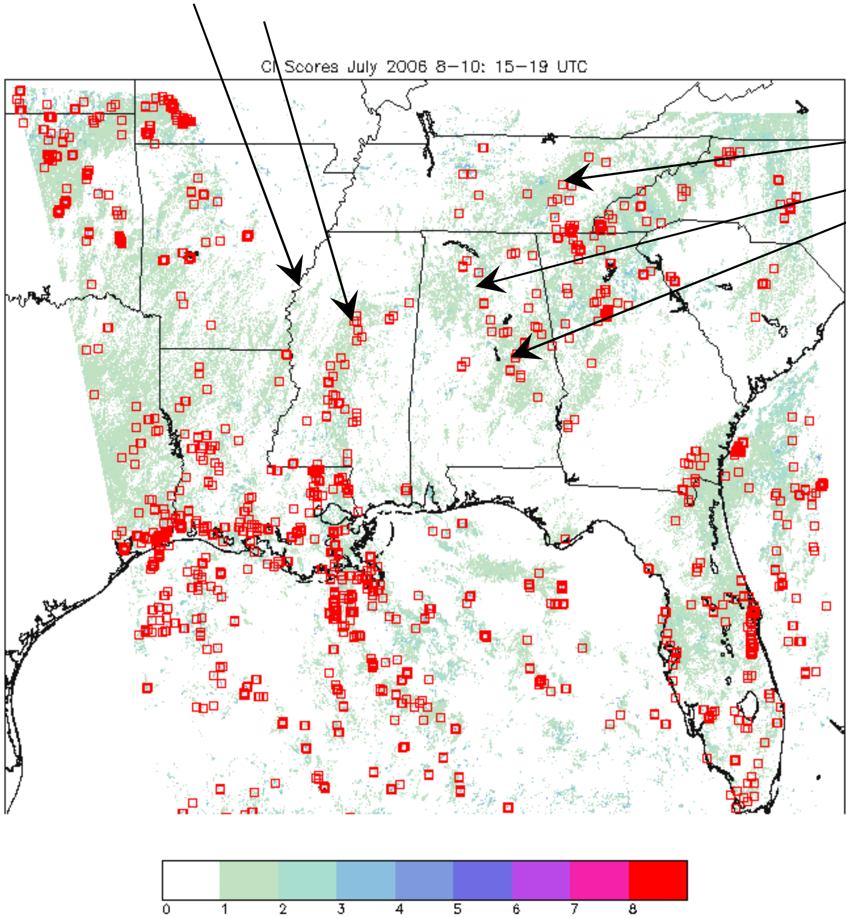
Inputs: (a) GOES-estimated solar insolation, (b) soil moisture (from models and/or estimated from antecedent rain) and (c) vegetation (health, NDVI).





Walker et al. (2009)

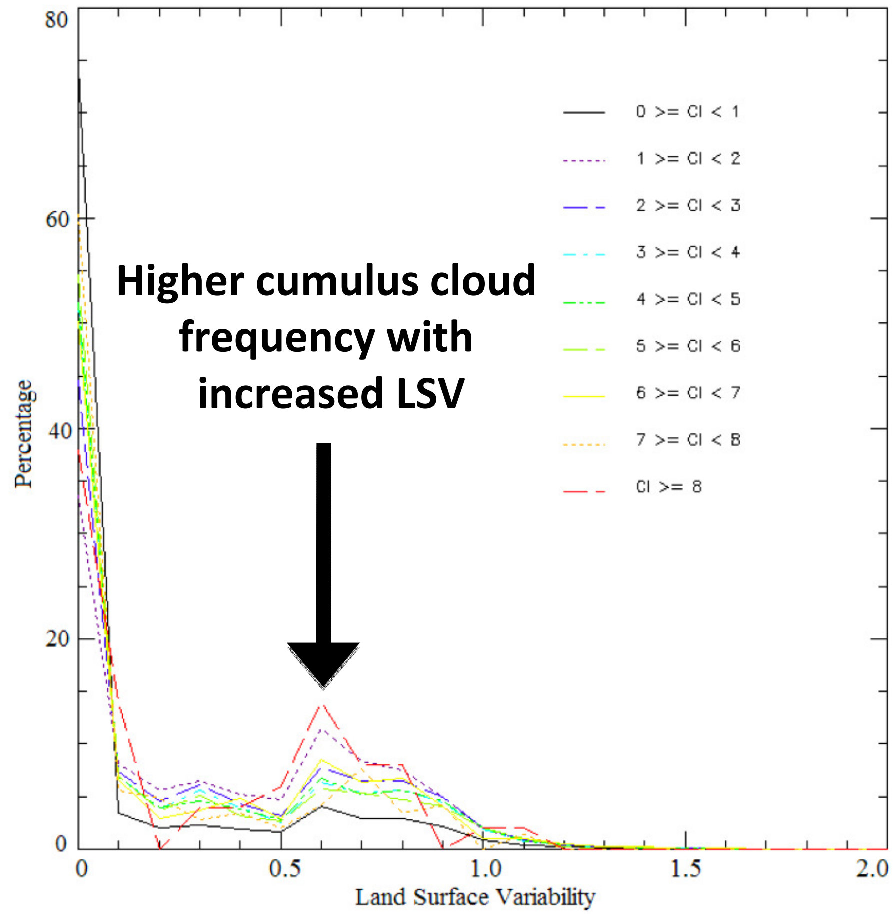
Land Surface Variability (LSV)



Topography-gradient signal

Convective Clouds vs LSV
15-19 UTC 6-14 July 2006

$$LSV = \frac{SD_{land\ cover\ height}}{Max(SD_{land\ cover\ height})} + \frac{SD_{elevation\ gradient}}{Max(SD_{elevation\ gradient})} + \frac{SD_{NDVI}}{Max(SD_{NDVI})}$$



7-day average MB06 CI scores:
Red= score ≥ 5

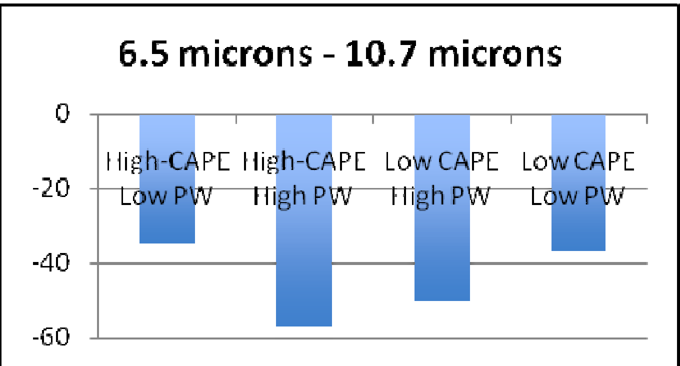
CI Scores correlated with topography, vegetation, & land-cover: *Physical forcing for cumulus updrafts*.

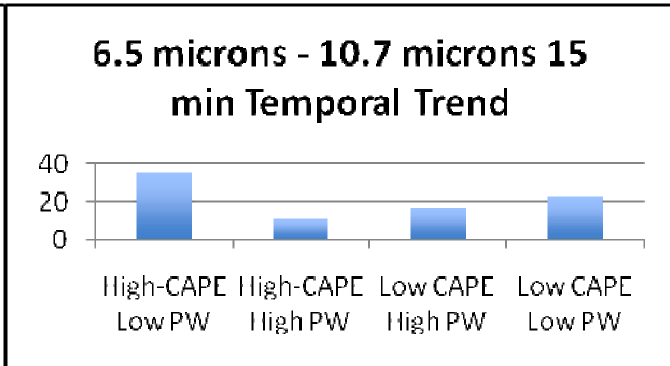
Gambill and Mecikalski (2011)

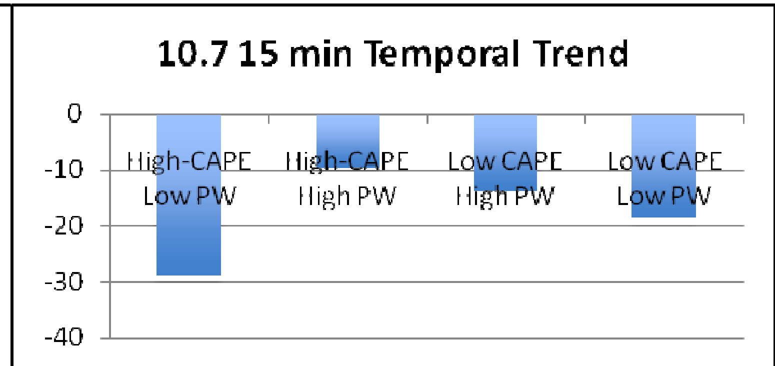
Leveraging ROSES 2007 Results:

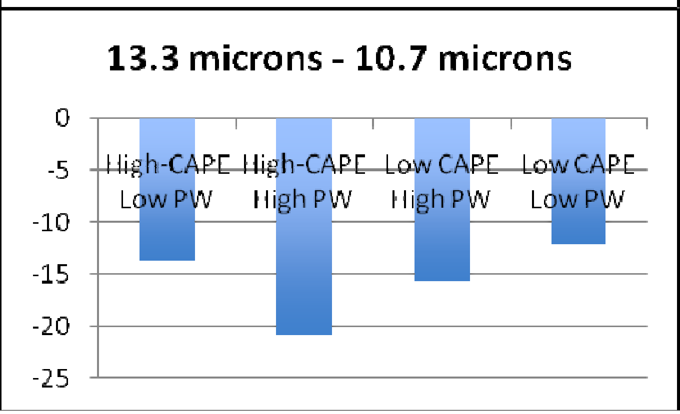
Enhancements to SATCAST Interest Fields

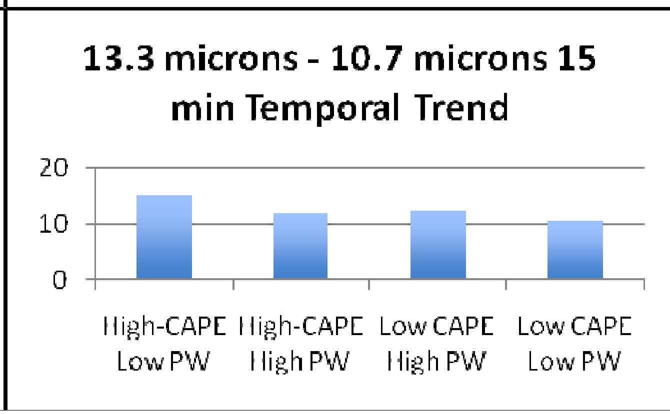
1. Precipitable Water (PW) has shown to have most impact on interest fields. Viewing angle is another important impact on the interest fields.
2. High amounts of PW can cause some interest fields that use 10.7 μm to miss due to water vapor absorption in that channel.
3. Regional adjustments to IR interest fields help avoid use of uniform thresholds.
4. Solid determination that use of multiple interest fields is beneficial to reduce false detection, while some IR fields are unimportant in CI nowcasting.
5. Correlating IR fields to NWP datasets is difficult when expecting to bound CI nowcasting by environmental constraints.

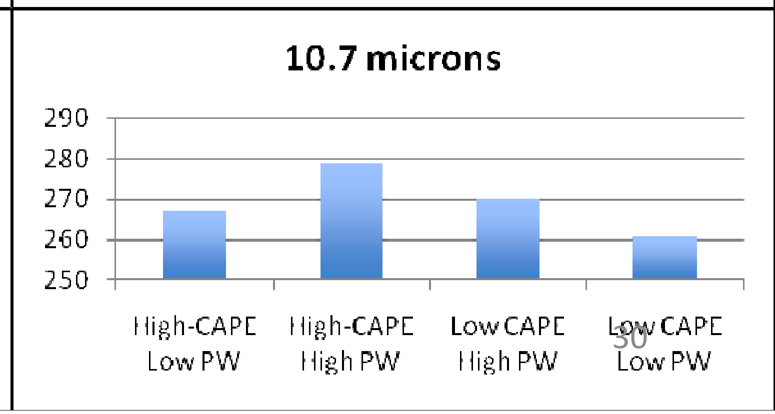












Near-term Plans

1. **Develop a case study approach, focusing on events of CI and LI over Gulf of Mexico and near-shore airports.**

2. **Couple 1-6 hour CI nowcasting to "storm intensity" estimates that leverage TRMM cell database, TRMM fields and LIS.**

3. **Populate the ANN model with MODIS estimates of soil moisture, and AMSR-E SST data, for 24 hr thunderstorm forecasting.**

4. **Basic research to better understand how to use IR and reflectance fields over oceanic regions to nowcast CI.**

from Donovan et al. (2008)