Environmental Analysis of GOES-R Convection Initiation Forecasting Algorithms

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Introduction

Forecasting convection initiation (CI) by satellite is an emerging technique with the enhanced temporal and spatial resolution of the GOES-R advanced baseline imager which has led to the development of two GOES infrared based CI forecasting algorithms; the University of Wisconsin-Madison cloud top cooling algorithm (UWCTC; Seiglaff et al. 2011) and the University of Alabama at Huntsville satellite convection analysis and tracking algorithm (SATCAST; Mecikalski and Bedka 2006). While several studies evaluate the effectiveness of the present algorithms (e.g. Hartung et al. 2013; Walker et al. 2013) no study has evaluated how satellite based CI forecasting would be affected by pre-CI environmental variables. Mecikalski et al. 2008 and Walker et al. 2013 have speculated on the effects of unfavorable convective environments on forecasting algorithm performance, however, no further research was been conducted. The present study analyzes the impacts of changing pre-convective environments on algorithm performance and takes advantage of an objective validation scheme developed by the University of Nebraska-Lincoln (see poster #688). Both SATCAST and UWCTC algorithms are validated and inferences from large scale study periods are applied via data fusion which should improve future satellite CI products.

Methodology

- SATCAST and UWCTC are first objectively validated for two study periods over the Great Plains (Figure 1)
- Pre-CI environmental variables are diagnosed from Rapid Refresh model data (Table 1)
- Data from the study periods are statistically examined between positive indications (indications with CI) and false indications (indications without CI) using principal components analysis and Mann-Whitney non-parametric tests
- Variables with statistically significant differences are applied to several case studies through a quadratic discriminant analysis (QDA) data fusion process
- QDA filtered products are examined for improvement using confusion matrices and percentage of improvement values (POI; difference between percentage of false alarms and positive detections filtered)
- Positive POI values indicate areas where CSI and Brier score values have increased

Table 1. List of variables used with respective abbreviations and descriptions.

Variable	Abbr.	Description
Convective available potential energy	CAPE	Total integrated positive potential energy calculated from the LFC to the EL
Convective Condensation Level	CCL	Level at which the surface mixing ratio meets the temperature profile
Convective inhibition	CIN	Total integrated negative (downward) potential energy from the lifted parcel level to the LFC
Equilibrium level	EL	Level above LFC where a lifted parcel becomes cooler than the surrounding environment
Lifted condensation level	LCL	Level at which a lifted parcel saturates
Level of free convection	LFC	Level where an adiabatically lifted parcel becomes warmer than the surrounding environment
Lifted Parcel Level	LPL	Level of maximum θ_e from the surface pressure to the surface pressure-300 hPa
LPL Divergence	LPLD	$\nabla \cdot \vec{V}$ composite value calculated at the LPL
Lapse rates	LR	Change in temperature with respect to height calculated at several levels (0-3 km, 700-500 hPa)
Mean Wind Differential	MWD	Change in wind speed and direction with respect to height calculated from several levels (0-6 km)
Normalized CAPE	NCAPE	CAPE divided by the depth of the unstable layer
Normalized CIN	NCIN	CIN divided by the depth of the stable layer
Layer Relative Humidity	RH	Average relative humidity calculated from the LCL to the LFC
Storm motion	SM	Averaged layer of mean wind from 0-6 km assumed to be the characteristic storm motion
Convective Environmental Difference	T_c-T_e	Approximation of cumulus field formation potential, the difference of the convective and environmental temperatures
EL-LFC	Z_{EL-LFC}	Distance in m from the LFC to the EL
LFC-LCL	$Z_{LFC-LCL}$	Distance in m from the LCL to the LFC

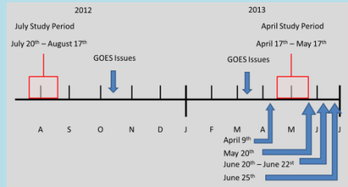


Figure 1. Timeline of data collection periods from July 2012 – July 2013 with study periods highlighted in red and case studies shown with blue arrows.

Results

- PCA revealed an apparent relationship between algorithm performance and instability (CAPE)/ stability (CIN; top two sources of variation) for both algorithms (Figure 2)
- Box plots for both SATCAST and UWCTC algorithms support the relationship of performance to instability/ stability (Figure 3)
- Inconsistent relationships are found between study periods for some variables such as LCL (Figure 3)
- Variable relationships are found by comparing box plots between study periods to total dataset Mann-Whitney derived significant differences
- Variables with significant differences are used in the quadratic discriminant analysis to improve future products

Table 2. Mann-Whitney P-Values for significant differences between positive and false indications.

	UWCTC	SATCAST
CAPE	0.000	0.000
CIN	0.000	0.000
LCL	0.008	0.000
LFC	0.000	0.000
EL	0.000	0.000
RH	0.000	0.000
LPL	0.455	0.108
LPLD	0.000	0.000
T_c-T_e	0.000	0.000
CCL	0.042	0.000
MID LR	0.009	0.000
LOW LR	0.000	0.000
MWD	0.000	0.057
NCAPE	0.000	0.000
NCIN	0.000	0.000
Z_{EL-LFC}	0.000	0.000
$Z_{LFC-LCL}$	0.000	0.000
SM	0.014	0.000

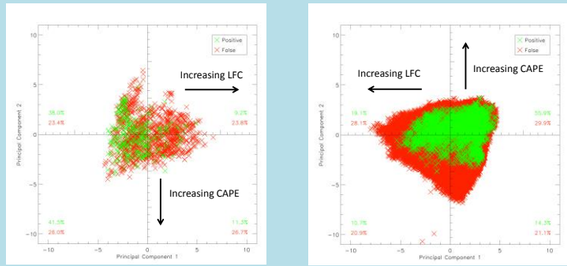


Figure 2. Plot of principal components for UWCTC (left) and SATCAST (right) with positive (green) and false (red) indications.

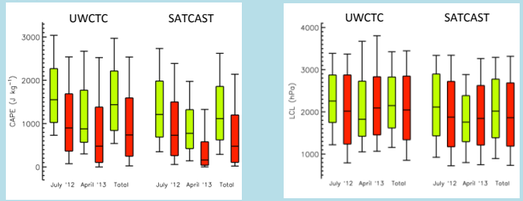


Figure 3. July, April and total UWCTC and SATCAST study period RAP CAPE (left) and LCL (right) values for positive (green) and negative (red) indications. Boxes represent the 25th to 75th percentiles and whiskers are from the 10th to 90th percentiles. Medians are shown as solid lines within the boxes.

Data Fusion

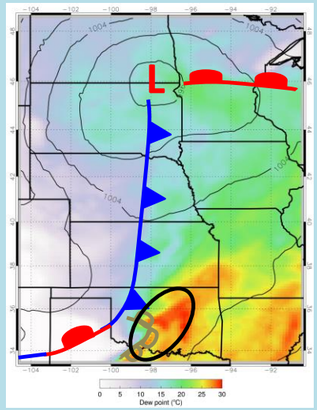


Figure 4. 1800 UTC 20 May 2013 RAP MSLP and surface dew point with surface boundaries. Black circle indicates area of severe/tornadic deep CI.

One of the case studies chosen was 1800 UTC 20 May 2013 to 0000 UTC 21 May 2013. A surface low located over the northern plains stalled with a cold front/stationary boundary draped from South Dakota to the northern Texas panhandle (Figure 4). A dry line present over west-central Oklahoma produced discrete supercells in a "classic" severe convective scenario. With CAPE values reaching > 5000 J kg^{-1} and strong 0-6 km shear, a supercell developed and spawned a deadly tornado in Moore, Oklahoma. This day was chosen to analyze NWP-fused CTC-based algorithms in a high CAPE/high shear environment where CI occurrences are high impact events.

Data fusion results :

- Several false indications correctly removed from the SATCAST and UWCTC datasets (Figures 5 and 6)
- Both SATCAST and UWCTC that are kept show impressive lead time in forecasting the strong updraft on the storm that produced the Moore, Oklahoma tornado (Figure 7)
- The QDA successfully discards extra indications in NE, and improves the positive to false indication ratio (Table 3)
- Positive POI values indicate improvements in overall CSI and Brier score values

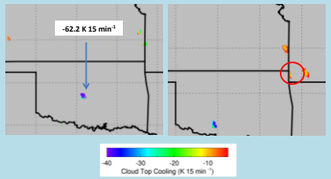
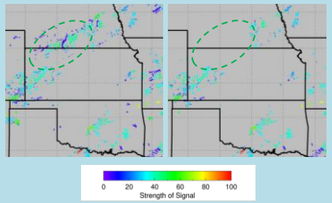


Figure 5. 1910 UTC 20 May 2013 UWCTC product with QDA filtering and the maximum value of measured cooling for the Moore, Oklahoma, tornadic supercell (left) and 1815 UTC 20 May 2013 example of correctly QDA-filtered UWCTC product circled in red (right).

Figure 6. 1825 UTC 20 May 2013 unfiltered (left) and QDA-filtered (right) SATCAST data. The green circle highlights an area where false detections are correctly removed.



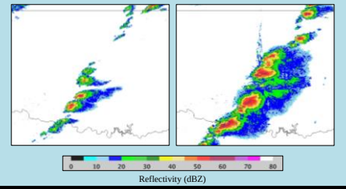


Figure 7. 1910 UTC 20 May 2013 NMQ reflectivity data (dBZ) over central Oklahoma (left) and one hour later (right).

Table 3. 20 May 2013 confusion matrices for SATCAST (left) and UWCTC (right) QDA filtered dataset with percentage of improvement (POI).

SATCAST MW

Actual \ Predicted	False	Positive	Total
False	9845	21031	30876
Positive	302	798	1100
Total	10147	21829	31976

POI: 4.43%

UWCTC MW

Actual \ Predicted	False	Positive	Total
False	15	79	94
Positive	7	70	77
Total	22	149	171

POI: 6.87%

Conclusions

Using various statistical methods on two large objectively validated study periods and five case study days filtered with a quadratic discriminant analysis technique, the following conclusions were reached:

- Analysis of all environmental variables through PCA along top sources of variation suggest that a relationship exists between algorithm performance and pre-convective environments
- MW testing and comparison of study periods through box plots suggest that CAPE, CIN, LPLD and T_c-T_e are useful variables to consider for environmental performance
- Positive detections are common in regions with more instability/less stability and more low level convergence
- Due to inconsistent relationships, no conclusions are made on the effects of LCL, CCL, RH, LR and MWD on algorithm performance
- Application of variables with statistically significant differences between positive and false indications through QDA improved new products in case studies
- Operational users of algorithm products should consider convergent regions with high CAPE and low CIN to be areas where satellite CI algorithms will perform well

While the objectives of this study were fulfilled, future studies on this topic can consider the following:

- Objective validation can be improved through the use of lightning detection at the launch of GOES-R
- Additional work can be done with models to experiment why certain environmental relationships were seen in this work
- Environmental relationships seen in this work can be revisited with GOES-R related products, when SATCAST and UWCTC are operational on the high temporal/spatial resolution of the new advanced baseline imager
- More data, more cases and more situations

Acknowledgements

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Data Sources

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