An Objective Validation Approach to Diagnose Environmental Effects on GOES-R CI Algorithms

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Introduction

The use of cloud top cooling (CTC) trends to forecast convection initiation (CI) was explored in Roberts and Rutledge (2003) who found through comparison of Geostationary Operational Environmental Satellite (GOES) imagery and Weather Surveillance Radar-1988 (WSR-88D) that the first 35 dBZ echo occurred approximately 30 minutes after large cooling rates were observed at the cloud tops of subfreezing (<0˚C) quasi-stationary cloud pixels. The discovery of nowcasting using CTC trends led to the development of two GOES infrared based CI forecasting algorithms. The University of Wisconsin-Madison cloud top cooling algorithm (UWCTC) uses a computationally inexpensive boxed averaging method to track cloud objects with logic to filter out horizontal motion based cooling (Sieglaff et al. 2011). The University of Alabama at Huntsville satellite convection analysis and tracking algorithm (SATCAST) by contrast uses mesoscale atmospheric motion vectors to track identified cloud objects and monitor several spectral trends known as interest fields (Mecikalski and Bedka, 2006; Walker et al. 2012). Several studies have validated these algorithms on a subjective basis and made environmental inferences based on these validations. An objective validation scheme would allow for a large sample size collection of CTC algorithm data. Large sample size collections are needed to determine if pre-convective environments have an effect on the performance of CTC based forecasts (see poster #687). It is not the purpose of this poster to objectively evaluate algorithm skill. This poster proposes an objective validation method only to separate indications into positive and false forecasts for analysis of pre-convective environments.

Methodology

The following datasets are collected for this study:

- SATCAST/UWCTC products to be validated
- National Mosaic Quantitative Precipitation Estimation (NMQ) mosaic radar (Zhang et al. 2011)
- Rapid Refresh (RAP)
  - Due to the low temporal resolution of the RAP, this study uses a 50 km radius mask (~7850 km^2) around all ongoing convection and considers these as contaminated areas
  - A 50 km radius ensures that convective events cannot advect into areas that are being considered for pre-convective environmental analysis

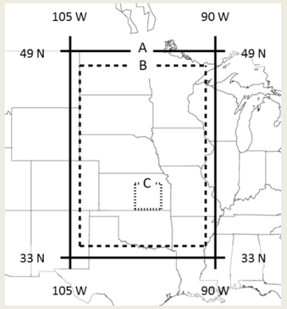

Figure 1. A) Total study area B) Validated study area, accounting for tracking issues along domain boundaries C) Hand validated domain

Validation first requires a definition for CI. Identification of convective events from raw NMQ data requires clustering (segmentation) of reflectivity into discrete countable cells. A subjective (hand) analysis of all CI events is performed within a small domain and compared to CTC based forecasts over a four hour time period on 25 July 2012 (figure 1 area C). Inferences from the hand validation are transferred into the objective validation over a larger domain (figure 1 areas A and B).

All datasets are remapped using a nearest neighbor approach (figure 2) for direct comparison. Once all grids are produced on the same map, the validation process can begin.

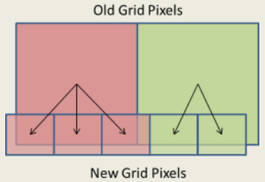

Figure 2. Example of nearest neighbor remapping technique

The k-means and watershed segmentation approach in the Warning Decision Support Services-Integrated Information (WDSS-II) suite is used in this study (Lakshmanan et al. 2009, figure 3). In this poster, CI is defined as the first occurrence of 35 dBZ reflectivity spatially covering a sufficient areal extent (evaluated in the hand analysis). The spatial constraint is applied to allow an automated approach to analyzing CI. Without the spatial constraint, several "noise" pixels could be identified as individual CI events. The segmented radar data are then tracked.

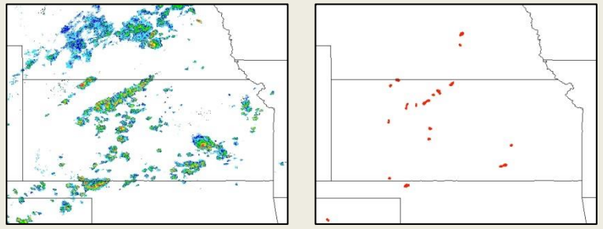

Figure 3. Example 4 km NMQ radar mosaic data (left). W2segmotion output with resolved convective clusters shown in red (right).

The Thunderstorm Observations by Radar tracking algorithm (ThOR) was developed by the University of Nebraska for the purposes of identifying and tracking convective cells (Houston et al. 2013).

- ThOR tracks clusters by identifying cells within an acceptable error range of a first guess centroid location (figure 4).
- ThOR considers all possible tracks and chooses the track with the lowest mean error.
- The initial resolved cluster of a track is considered the point of CI.

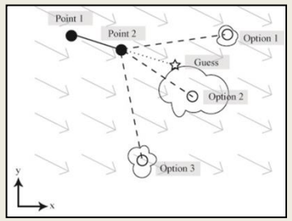

Figure 4. Schematic of ThOR tracking with NARR storm motion data. Given the initial guess, ThOR will build 3 tracks, and chose the option with the least amount of mean error (in this example, option 2). (Adapted from updraft.unl.edu/thor/wiki)

ThOR also tracks indications which accounts for multiple indications occurring on a single convective complex.

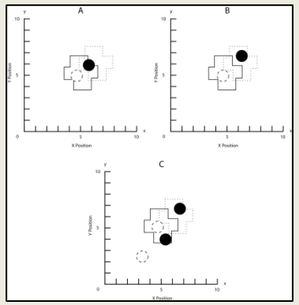

Figure 5. Three different environments (notated A, B and C) of validation areas (solid polygons) and a validation area that is advected forward (dotted polygons). Solid circles indicate locations of CI, and dashed circles indicate original cloud object location.

Upon completion of tracking and segmentation, validation is performed using the following steps:

- An indication that corresponds with the resolved CI cluster location within one hour is considered a positive detection.
- If an indication occurs with no corresponding CI event, then that indication is considered a false alarm.
- Since the objective of this work is to classify indications as good forecasts, any indication that occurs on an event after CI has been detected is considered a false alarm.
- Validation processes account for indication complex advection (figure 5) and possible parallax errors.
- With objective settings tuned, tracked indications will produce a usable classification of groups into positive and false detections for environmental analysis.

Results

- The subjective (hand) validation revealed optimal settings for the WDSS-II clustering algorithm (table 1) and found similar skill scores to Hartung et al. 2012.
- The objective validation technique used in this work was found to produce substantially lower skill values for both UWCTC and SATCAST than was found in Sieglaff et al. 2011, Hartung et al. 2012 and Walker et al. 2012.
- Upon further inspection it was found that low skill scores in objective validation were directly a result of the exclusion of indications that occur on convective systems after CI was detected.

Table 1. Validation of WDSS-II/ThOR CI clusters compared to subjectively identified truth CI clusters. WDSS-II settings presented as low smooth (50th percentile smoothing over a 5x5 box), medium smooth (50th percentile smoothing over a 7x7 box) and high smooth (50th percentile smoothing over a 9x9 box).

WDSS-II Settings	Min. Scale	POD	FAR	CSI
High Smooth	20	73.1	20.4	63.5
Med Smooth	30	69.7	18.6	66.67
Low Smooth	40	62.7	18.6	61.2

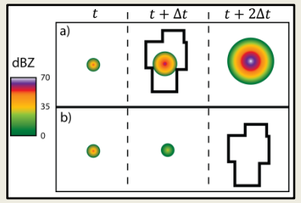

Figure 6. Radar schematics (in dBZ) including three time steps with initiation at time *t* for a) an example of a positive post CI CTC indication, where reflectivity values intensify after cooling and b) an example of a false CTC detection occurring after CI, with no nearby ongoing convection. Black outlined polygons represent CTC indications.

If a similar approach is applied on our objective validation as was in Hartung et al. 2012 where we allow successful CTC indications for a 17 minute period after CI detection, we find validation produces similar numbers to previous findings (FAR values around 40%, POD around 50%). However, allowing for successful CTC indications after CI *provides no benefit to environmental analysis* and risks of contaminating environmental data with respect to performance (figure 6). All successful post CI CTC indications occur within close proximity to ongoing convection, and therefore are excluded from an environmental analysis regardless of positive or false classification. False post CI CTC detections are not always in close proximity to ongoing convection, and therefore could be included in an environmental analysis. It is crucial to classify these points as false for a correct assessment of environmental effect on CTC algorithm performance with a model that cannot resolve convective time scales. Therefore, objective validation produces usable positive and false indication datasets for environmental analysis (figure 7).

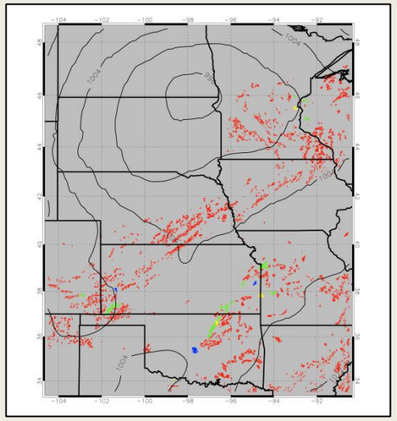

Figure 7. 1910 UTC 20 May 2013 Example of validated UWCTC and SATCAST data one hour before the Moore, OK tornado with contoured MSLP in hPa. Positive indications are shown in green (blue) for SATCAST (UWCTC). False indications are red (yellow) for SATCAST (UWCTC).

Conclusions

Objective validation of CTC indications is made possible through the comparison of WDSS-II clustered/ThOR tracked NMQ data to CTC based indications. Through the methodology used in this poster, the following conclusions were reached:

- Since the objective methodology follows a consistent approach to validation, it can be used to evaluate changes in performance with respect to data fusion filters (figure 8)
- Through implementation of objective validation, a validation paradox was found
  - It is not possible to evaluate both algorithm skill and environmental performance changes using an NWP that cannot resolve convective time scale changes.
  - Excluding CTC indications that occur after CI detections reduces overall skill scores, and is necessary to prevent contamination of positive detection environmental data through post convection CTC indications, and therefore should be used to evaluate pre-convective environments with respect to positive and false CTC indications (for true skill evaluations, the reader is referred to Hartung et al. 2012 for UWCTC, and Walker et al. 2012 for SATCAST)

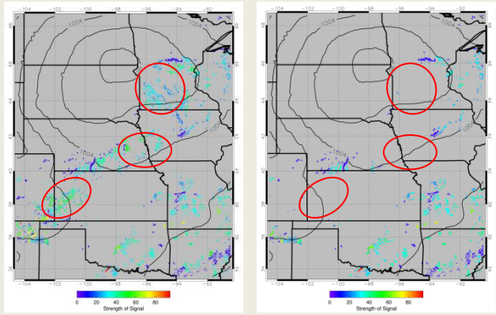

Figure 8. 1825 UTC 20 May 2013 example of discriminant filter application to SATCAST data. Brier scores from the unfiltered dataset (left) can be compared to Brier scores of the filtered dataset (right). If values are calculated with a consistent method, improvements in the Brier score can be seen as overall improvements to the dataset. Red circles indicate areas where false alarms are successfully filtered.

Acknowledgements

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Data Sources

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