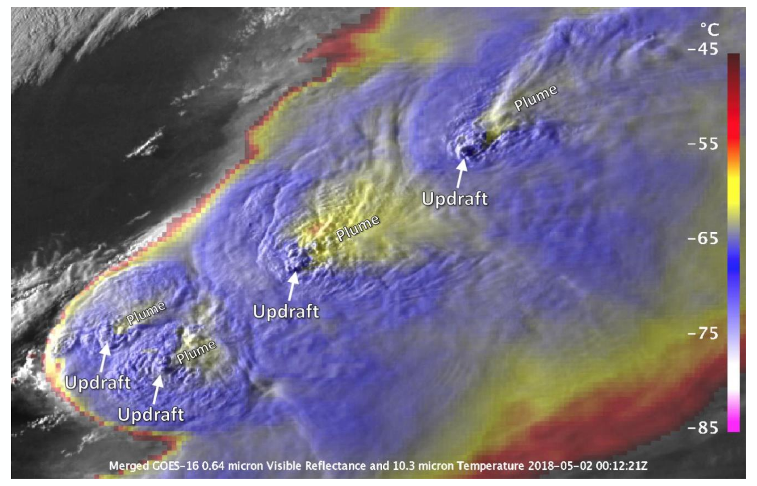

Automated Detection of the Above Anvil Cirrus Plume Severe Storm Signature with Deep Learning

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Introduction and Objective

The above anvil cirrus plume (AACP) is a cloud phenomenon that is generated by an intense tropopause-penetrating updraft which injects cirrus clouds into the stratosphere up to several kilometers above the primary storm anvil outflow layer. Storms that have such intense updrafts are often supercells which generate severe weather such as tornadoes, high winds, and hail. In fact, an AACP is also the strongest indicator of a severe storm documented to date in visible and infrared (IR) imagery [2]. In addition, AACPs moisten the stratosphere perhaps much more so than storms without AACPs which has an impact on the Earth's radiative balance [1].

AACPs typically appear anomalously warm and uniquely textured in satellite imagery. Though an AACP can be identified by the human eye, no automated AACP detection methods currently exist. Lack of detection inhibits understanding of where and how often AACPs occur and how these storms influence stratospheric air composition. Previous work involved synthesis of multiple remote sensing and severe weather report/warning data sources to identify AACPs in Geostationary Operational Environmental Satellite system (GOES) imagery and better understand their weather impacts [2]. This current study demonstrates a proof-of-concept automated AACP identification method based on the application of a deep learning segmentation model known as a U-net. This study documents the development of a U-net model capable of identifying emergent AACPs using only satellite IR and visible reflected sunlight imagery. The performance of a U-net is quantitatively benchmarked with human AACP identifications and qualitatively assessed through animations of detections generated from GOES-16 1-minute temporal resolution imagery.

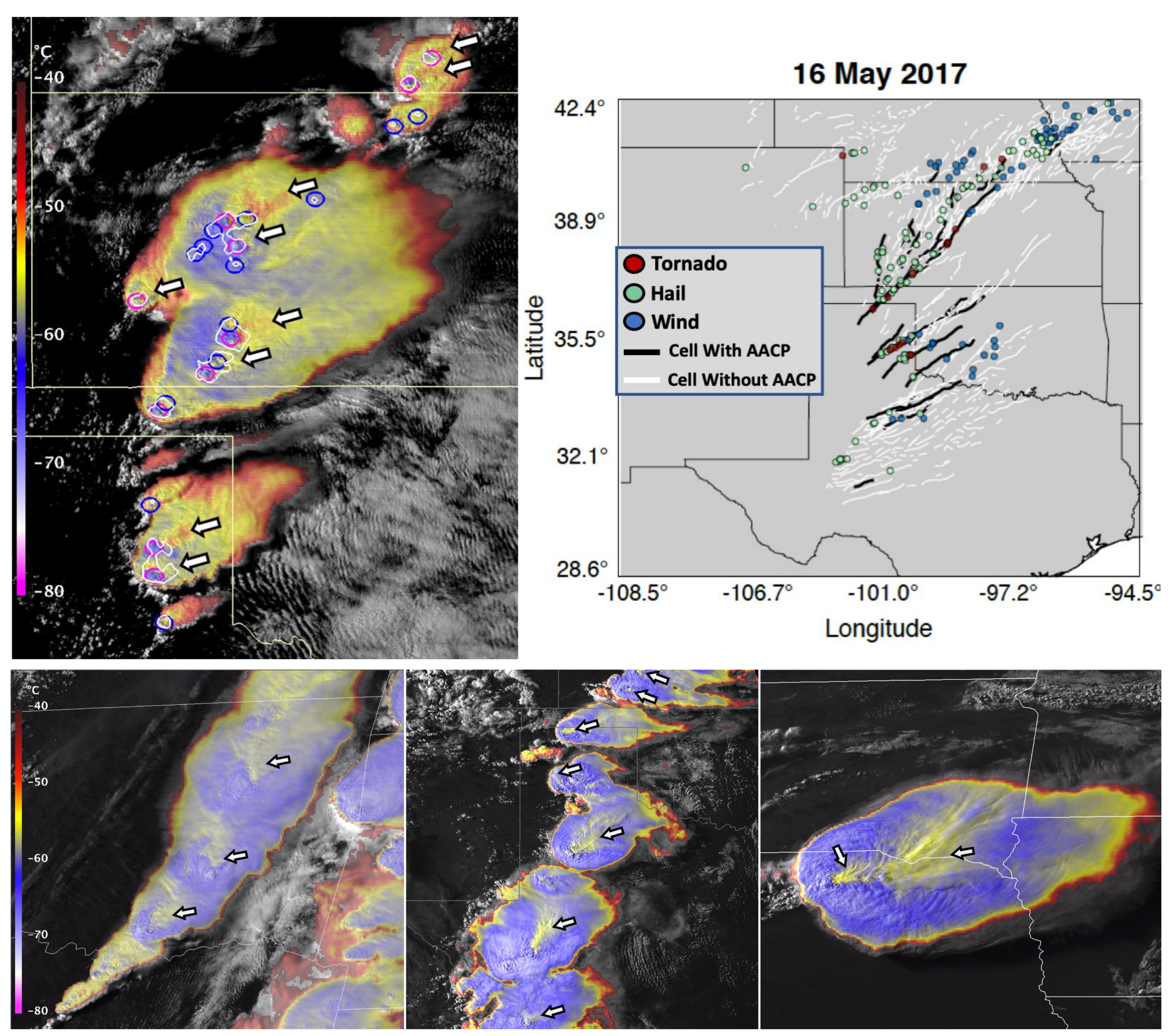

Fig 1. (TOP) (left) GOES-16 merged visible and IR imagery on 16 May 2017, overlaid with AACP (magenta circles) and non-AACP (blue circles) producing storm cells identified using GridRad 40 dBZ echo top heights. GridRad echo tops reaching a 13 km altitude and above the tropopause are also shown (white contours). (right) A map of AACP (black) and non-AACP (white) cell tracks throughout the duration of the 16-17 May 2017 severe storm outbreak, overlaid with severe weather reports, showing that severe weather is often concentrated along AACP tracks. [2]

(BOTTOM) Examples of AACP producing storms over the U.S. on three randomly selected days. White arrows on the GOES images point to AACPs

Data and Methodology

Data Preparation:

Imagery
- IR and VIS imagery only
- IR, VIS, and ENTLN lightning flash extent density

Preprocessing
- Automated storm tracking of 40 dBZ storm cells in NEXRAD GridRad data [3, 5]
- IR data normalization
- VIS contrast limited adaptive histogram equalization (CLAHE) preprocessing
- ENTLN lightning flash extent density normalization

Time series and Relational Data
- Human labeling 2 classes (AACP and non AACP storm cells)
- Solar Zenith Angle (SZA) < 82 for reliable VIS data

Model:
- U-net
  - U-nets are deep convolutional neural networks that take a raw image as input and produce a segmentation map as an output. U-nets are especially effective at detection of highly nuanced spatial features within an image. This model has been shown to achieve great results despite a small training set. [4]

Fig 2. Diagram of the neural network used (U-Net). This model consists of a series of convolutional layers followed by max pooling operations which downsample the original image's dimensions. These layers are followed by upsampling layers with concatenation skip connections connecting the previous corresponding downsampling layers. The model eventually upsamples back up to the original image dimensions to predict probability of AACP occurrence on a pixel by pixel basis.

$$\text{IoU} = \frac{\text{TP}}{\text{FN} + \text{TP} + \text{FN}} = \frac{\text{area of intersection}}{\text{area of union}}$$

Analysis:

Quantitative
- Benchmarked against human labeling with 6 fold cross validation
- Metrics: IoU
  - The primary metric used for quantitative evaluation was Intersection over Union (IoU) with optimal probability threshold tuning.

Qualitative
- Visual assessment of performance on static imagery and animations to confirm colocalization of AACP labels generated using the models with that of human labeling in addition to assessing the prevalence of false positives and false negatives.

Results

Quantitative:
- The average IoU over all 6 folds was 0.33126 for the best performing model. The best performing model was the U-Net with IR and VIS data input for predicting updrafts and plumes. Ideally, we would like to see IoU reach 0.50 for future work.

Day	2017087	2017095	2017136	2017138	2017179	2017180	Average
IoU	0.28538	0.40495	0.37995	0.32163	0.26869	0.32694	0.33126

Table 1: Validation IoU results of the best performing model for each day of the dataset using 6 fold cross validation.

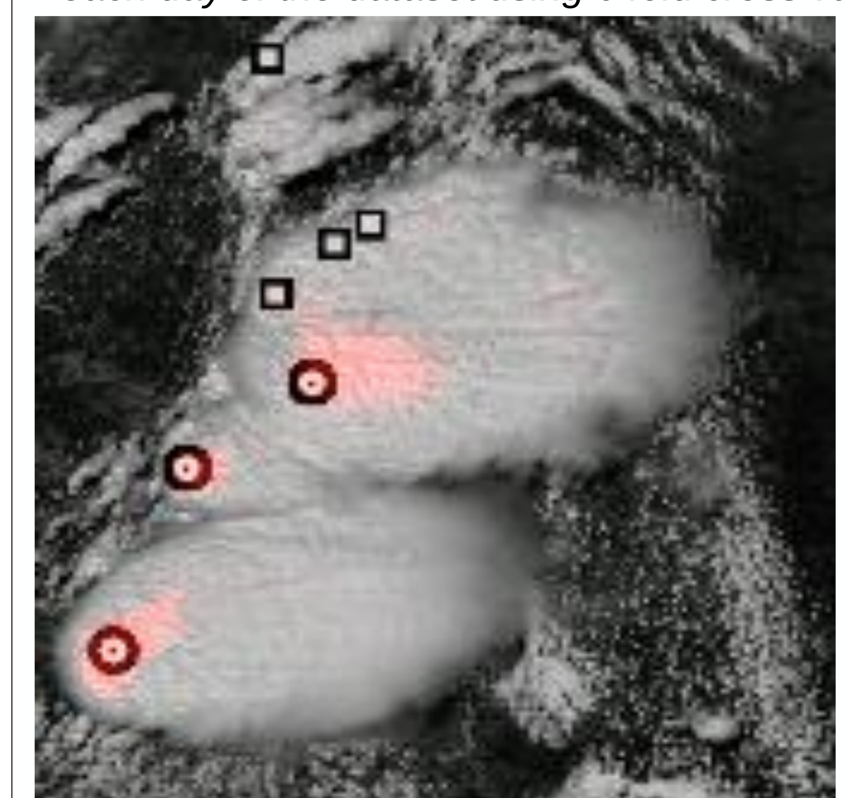

Fig 3. Sample model output. Ground truth labels (circles for AACP storms and boxes for non AACP storms) overlaid on top of prediction output and VIS imagery. The region predicted by the model to enclose an AACP is indicated by a reddish hue.

Qualitative:

IoU is a common metric used for the evaluation of semantic segmentation models. This metric alone does not convey an accurate picture of the performance of this model. Labeling the precise onset, cessation, and physical boundaries of fluid phenomena such as AACPs can be highly nuanced and somewhat debatable even among trained experts. Therefore, a qualitative assessment approach was also utilized in this study in order to determine the model's real-world utility.

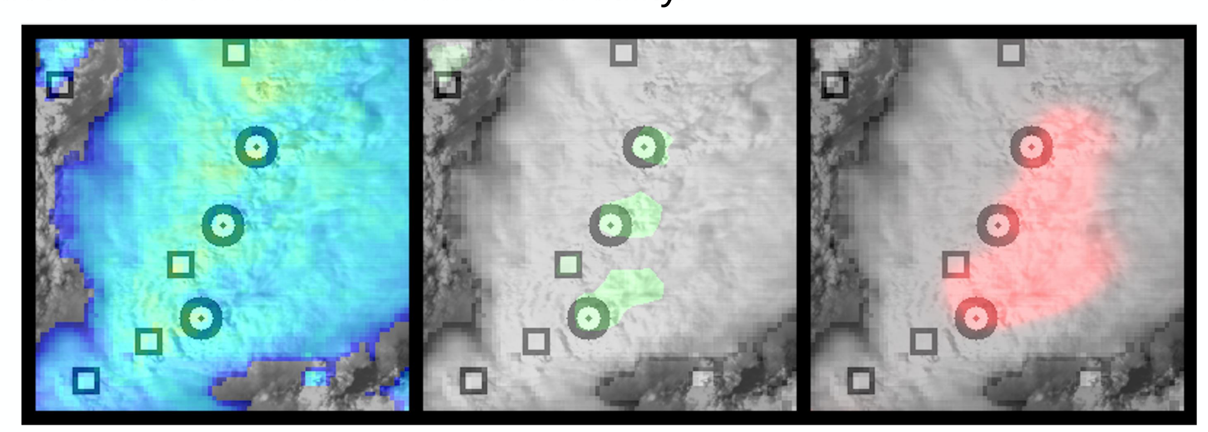

Fig 4: From left to right: Input image, hand labeled mask, model prediction. Rectangular markings represent non-AACP storms while circular markings represent AACPs. IoU = 0.225.

The challenge with IoU in capturing the true performance of this model is evident when comparing the middle image and the right image in figure 4. The intersection over union is diminished when comparing the area of any one of the 4 green hand labeled regions with the entire prediction mask area in red. However, the model's prediction appears to be accurate. It consistently identities plumes ejecting from active AACP updrafts. The predicted AACP areas originate from the updraft and predict a plume downrange of the updraft. It is only in the size of the predicted plume regions that the model is penalized by the IoU metric.

Conclusion

Above anvil cirrus plumes (AACP) often precede severe weather events such as tornadoes and severe hail. Automated detection of AACPs using satellite imagery alone would aid in the early detection of such events even in regions of the world where weather radar coverage is lacking. An automated detection mechanism would also improve understanding of the climatology of AACP storms and their impact on stratospheric composition. Using visible, IR, and lightning satellite imagery as input into a U-Net deep convolutional neural network with radar-derived storm cell tracks and human AACP identifications as training output, we were able to achieve promising automated detection of AACPs.

Future Work

- Fully convolutional network and long short-term memory (FCN-LSTM) network for time series. [6]
- Re-training model to discriminate overshooting storms with AACPs from overshooting storms without AACPs
- Tune probability thresholding
- Metamodeling with multiple different models using different inputs, IR alone, VIS+IR, VIS+IR+Lightning, and various combinations
- Exploring the capabilities of the Google Cloud Platform (GCP) AutoML Video Intelligence

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