

Airmass Properties from GOES ABI Using Machine Learning



Kyle Hilburn and Steve Miller

Cooperative Institute for Research in the Atmosphere

Kyle.Hilburn@colostate.edu

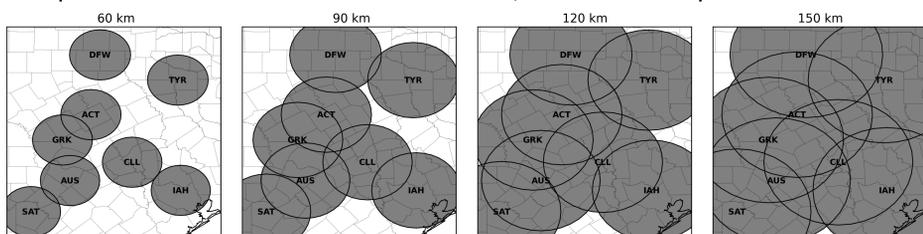


Introduction

Convective-scale numerical weather prediction (NWP) of severe weather phenomena is a very challenging forecast problem with impacts on life and property. It is an area where human forecasters add considerable value by interpreting NWP outputs together with loops of visible satellite imagery from GOES Advanced Baseline Imager (ABI) to increment the location and timing of convective initiation and subsequent severe weather. Our hypothesis is that machine learning (ML) could be used to provide automated estimates of these increments to assist human forecasters.

Data and Methodology

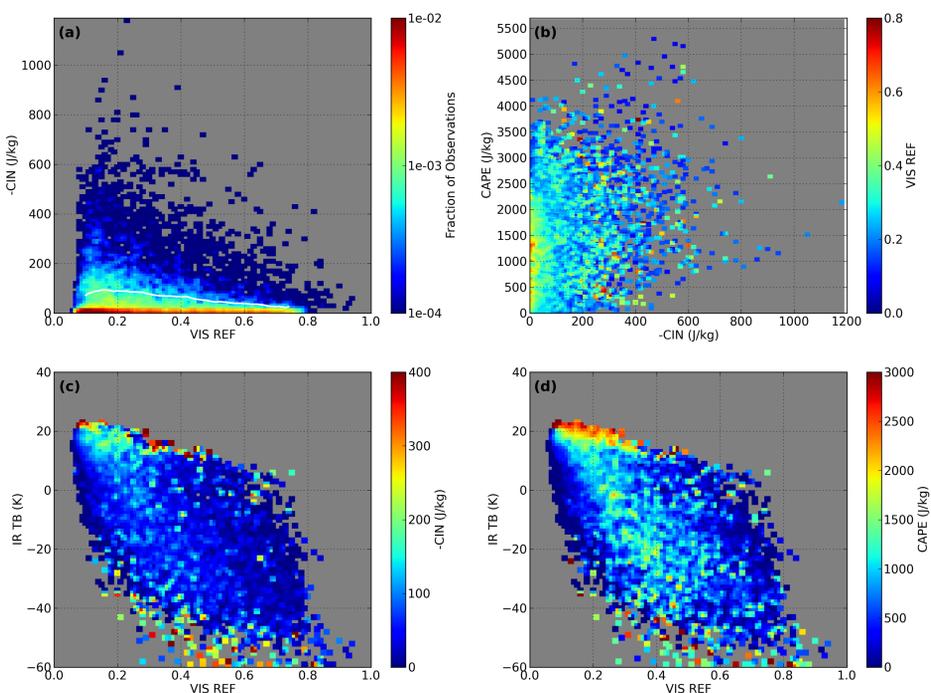
The training data for this exploratory study are HRRR 1-hour forecasts of convective inhibition (CIN) and convective available potential energy (CAPE) at each hour during the daytime. Input data to the ML algorithms come from spatial filters applied to GOES ABI imagery, and the figure below shows an example over Texas of the four radii tested; results in this poster used 120 km.



This initial evaluation focuses on the period April-June 2018, during daytime, over the eastern and central portions of CONUS. The first step in this investigation is feature construction and selection, discussed in this poster. Since ML contains no physics, in order to prevent generalization problems it is important at this step to construct a simple physical model of the phenomena and relate the different stages to what they look like in imagery. The second step is to use ML to construct the mapping from satellite properties to airmass properties. We seek to produce two continuous variables as outputs: an estimate of each of the airmass properties of interest and a confidence estimate characterizing the satellite information content for each situation.

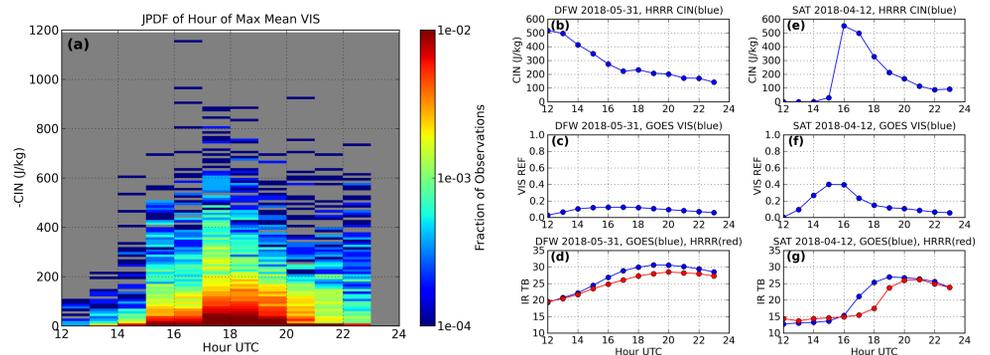
Results and Discussion

First we seek to answer whether there are daily-scale relationships between satellite and airmass properties. The figure below shows the daily-maximum (or minimum for IR TB) of the hourly-average properties.



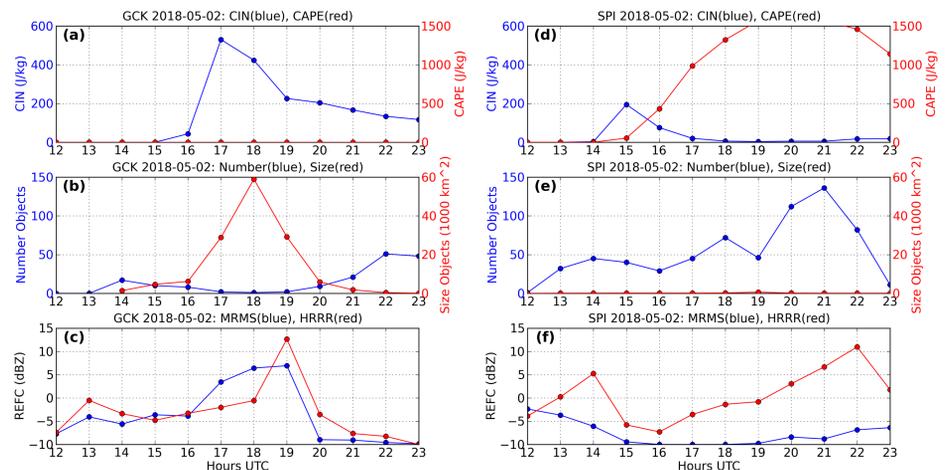
Panel (a) shows that there is an inverse relationship between CIN (times -1) and visible reflectance (VIS), where higher CIN is associated with smaller daily-maximum VIS. **Panel (b)** gives the mean daily-maximum VIS versus CAPE and CIN. The highest VIS values are scattered in the region of CIN > 200 J/kg across all CAPE, indicating that a certain amount of CIN is helpful in developing deep convection. **Panel (c)** provides mean daily-maximum CIN versus IR TB and VIS. The highest CIN values are found either for clear days (dark and warm) or stormy days (bright and cold). **Panel (d)** presents mean daily-maximum CAPE versus IR TB and VIS, showing that high CAPE is either associated with deep convection or may not be realized.

Next we seek to answer whether hourly-scale information in the statistical moments of satellite properties provides additional useful information. The figure below provides a joint histogram of the maximum daily CIN versus the hour of maximum VIS in **Panel (a)** and time series examples for Dallas in **Panels (b,c,d)** and San Antonio in **Panels (e,f,g)**.



Panel (a) shows the typical daily progression of VIS follows the solar cycle with peak near local noon. However there is a subset of high CIN cases with a peak near 15Z. Based on multi-spectral GOES imagery we identified these cases as stratus under a morning inversion, with additional confidence coming from the smooth texture and edge-to-center pattern of dissipation. The Dallas example exhibits erosion of CIN in **Panel (b)** with good agreement between HRRR and GOES in **Panel (d)**. The San Antonio example finds HRRR picking-up on the CIN by 16Z in **Panel (e)**, but large CIN was likely present before then. This appears to lead to a delay in stratus dissipation in HRRR relative to GOES in **Panel (g)**.

Finally we seek to answer what additional information is present in the time evolution of the spatial distribution of satellite properties, using an object based analysis. The figure below gives examples from the same day for Garden City, KS in **Panels (a,b,c)** and Springfield, IL in **Panels (d,e,f)**.



For Garden City, HRRR exhibits an increase in CIN at 17Z in **Panel (a)**, which is at odds with the jump in GOES cloud object size in **Panel (b)** indicative of convective initiation. This appears to lead to a delay in the development of deep convection in HRRR in **Panel (c)**. Over Illinois, HRRR has high CAPE and relatively low CIN in **Panel (d)**, leading to a spurious outbreak of strong popcorn convection. GOES shows the clouds remained very small in **Panel (e)** and HRRR overestimates reflectivity relative to MRMS in **Panel (f)**.

Summary and Conclusions

This work has demonstrated that information on thermodynamic parameters related to cloud development and suppression is present in GOES ABI imagery. We showed daily-scale relationships between maximum values of HRRR and GOES parameters. We examined the information present in hourly variability of GOES parameters, identifying a case of good agreement between HRRR and GOES, and another case where HRRR has a delay in erosion of the cap. We found that the time evolution of GOES cloud object properties is useful in monitoring the convective initiation process and spurious convection.

Some issues to address in our further research are:

- Using GOES derived products (using COD and CTH, rather than VIS and IR)
- Identifying additional NWP features to aid interpretation
- Identifying additional relevant cloud object properties
- Assessing stability measures not based on parcel theory
- Using split window moisture pooling information (in collaboration with Jack Dostalek and Louie Grasso at CIRA)

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