



Using Unsupervised Learning to Identify Severe Weather Regimes at Cape Canaveral

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Overview



- Background/Motivation
 - Mission Understanding
 - Data Acquisition
 - Data Understanding
- Methods
 - PCA
 - K-Means Clustering
- Analysis and Results
- Conclusion



Motivation







If we accurately predict severe weather at KSC and CCSFS, we can prevent costly rocket hardware damage and launch delays





A quick meteorological background



What is a severe thunderstorm?

The National Weather Service defines a severe thunderstorm a thunderstorm that produces any of the following:



A tornado



Wind gusts in excess of 58 mph (damage can be used as a substitute)



Hail greater that is at least 1" in diameter (quarter-sized) or larger







NWSNewOrleans

NWS New Orleans/Baton Rouge







Mission Understanding

- 45th Weather Squadron (45 WS) provides all operational weather support to KSC and CCSFS
- Some differences from NWS severe definition
 - Any size hail on KSC
 - ¾" on CCSFS
 - Wind speed verifiable up to 200/300ft (instead of 30ft)
- Launch Weather Officers issue severe forecasts for ground and launch operations; when rocket is exposed
- 45 WS has legacy forecast tools for lightning and severe weather







My Approach



- Research Question: Using the 1500Z (1100am) weather balloon (sounding), can we identify different severe weather regimes?
- Features: all derived from the morning weather balloon launched daily from Cape Canaveral (KXMR)
 - Various parameters and indices that measure the ingredients needed for severe weather
- Only used days when severe weather occurred





Data Acquisition



- Weather balloon data
 - Acquired via a request to the 14th Weather Squadron (climate unit)
 - Indices calculated from Python's MetPy library
- Pulled NWS severe reports from Iowa State University archive
- 45 WS severe warnings
 - Internal 45 WS database for all Warnings, Watches, and Advisories
- Wrote Python script to filter, and convert to a 0 or 1 for each day
- Merged datasets on date
- Only used days with severe weather (1 label)







Data Understanding





Candidate Predictors



- 41 candidate predictors from 15Z sounding
- Measures of temperature, wind, wind shear, moisture, and instability at various altitudes



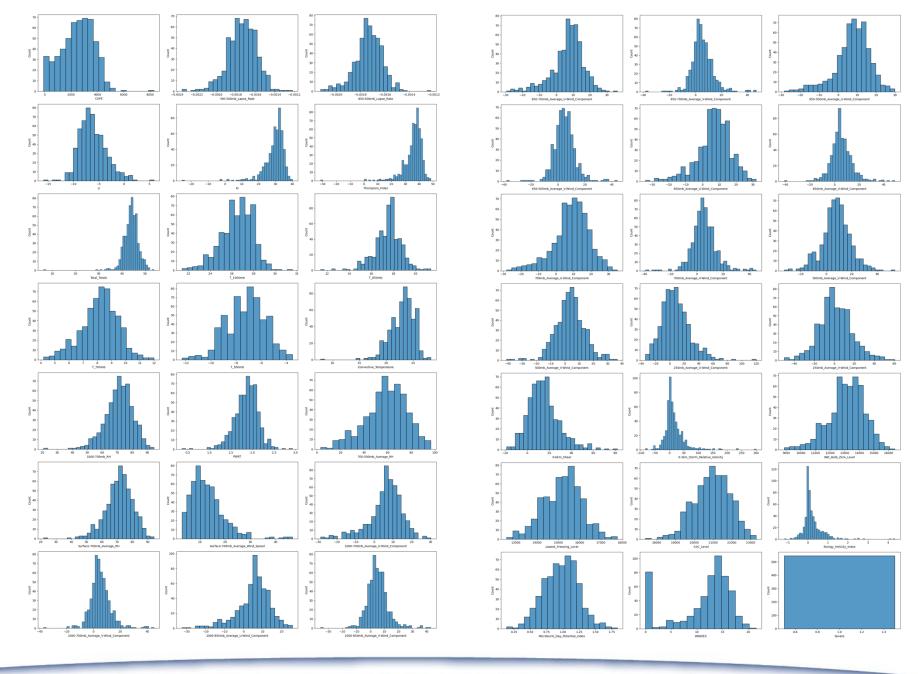
Subsetting the Data



- Limited to just the Wet/Thunderstorm Season
 - May thru September
- Limited to just days when severe weather occurred within 30 miles of CCSFS/KSC







SET THE PACE FOR SPACE







Methods





Data Preparation



- Removed several candidate predictors
 - · Reasons: too many null values, redundant, very highly correlated
- Removed obvious data errors



LAUNCH

Modeling Approach



- PCA
- K-Means Clustering







Principal Component Analysis



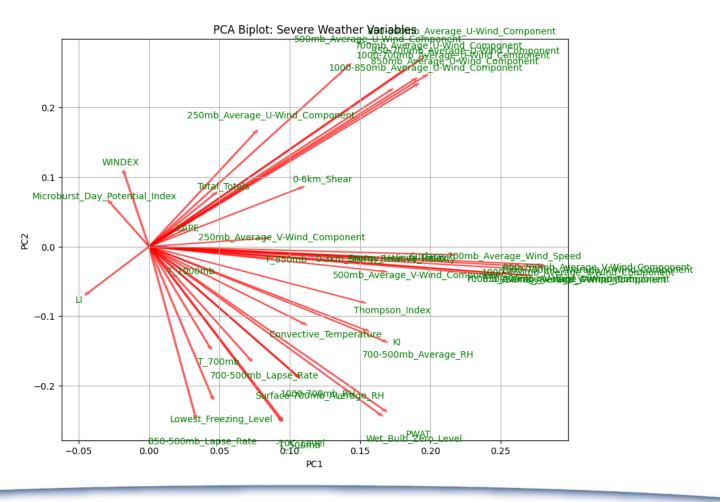
- PCA reduced 40+ variables to two main components:
 - PC1: Instability and moisture (e.g., CAPE, PWAT, TT)
 - PC2: Kinematic support (e.g., shear, SRH, winds aloft)
- PCA enabled clearer visualization of regime structure





PCA Biplot



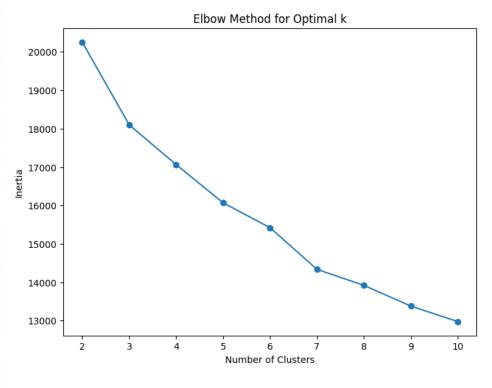


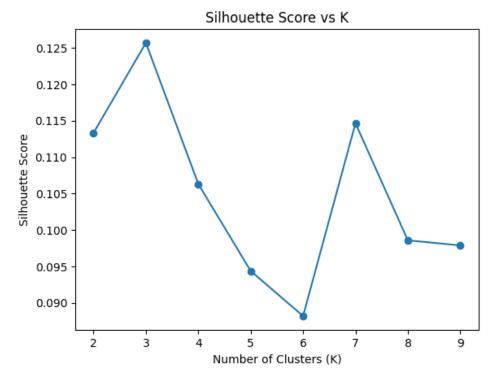




K-Means Clustering





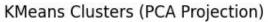


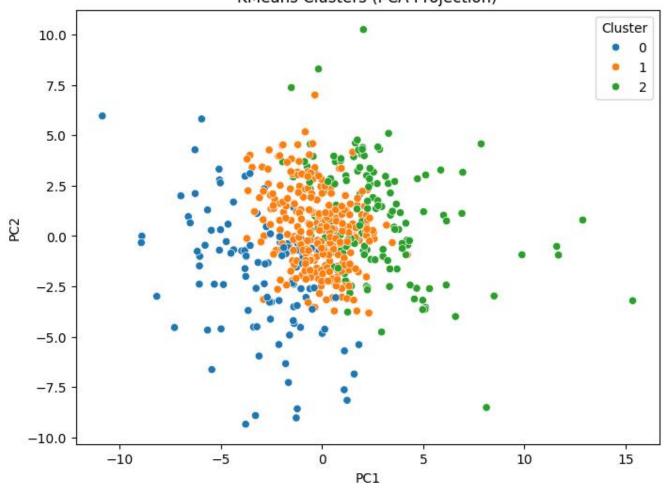




K-Means Clustering









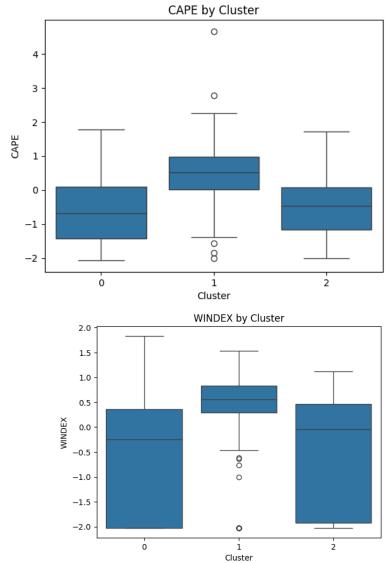


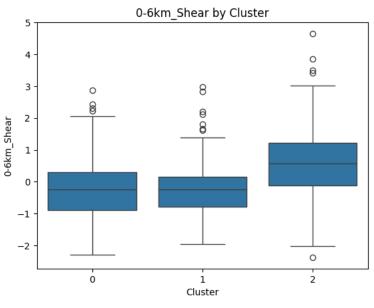


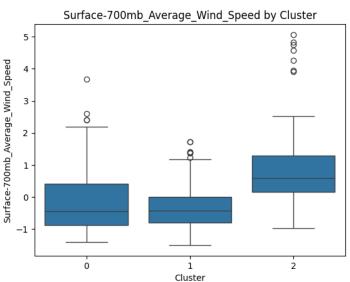
Analysis/Results















Model Evaluation



- Identified 3 primary regimes among severe events:
 - Cluster 0: Cool, weakly unstable environments
 - Cluster 1: Moist, warm-season pulse storm setups
 - Cluster 2: Dynamically forced, sheared environments
- Regimes suggest differing forecast concerns and storm modes.







Conclusion





Conclusion



- This work has potential to improve operations this summer
- Helps forecasters anticipate what *kind* of severe setup is present.
- Supports situational awareness potential severe weather days.
- Future work: Link regimes to individual threat types or add seasonal clustering.
- PCA + clustering provides a valuable lens on severe weather variability.