



# Use of Geostationary Infrared, Passive Microwave Imager, and Reanalysis Datasets to Assess Climatological Hailstorm Risk

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Kristopher Bedka<sup>1</sup>, Kyle Itterly<sup>2</sup>, Benjamin Scarino<sup>2</sup>, Konstantin Khlopenkov<sup>2</sup>, Douglas Spangenberg<sup>2</sup>, John Allen<sup>3</sup>, Cameron Homeyer<sup>4</sup>, Sarah Bang<sup>5</sup>, and Daniel Cecil<sup>5</sup>

<sup>1</sup> NASA Langley Research Center, Science Directorate, Hampton, Virginia  
<sup>2</sup> Science Systems and Applications, Inc., Hampton, Virginia  
<sup>3</sup> Central Michigan University, Department of Earth and Atmospheric Sciences, Mount Pleasant, Michigan  
<sup>4</sup> University of Oklahoma, School of Meteorology, Norman, Oklahoma  
<sup>5</sup> NASA Marshall Space Flight Center, Earth Science Branch, Huntsville, Alabama

## Introduction and Motivation

Geostationary satellites routinely observe deep convective cloud tops across the globe at high spatio-temporal resolution throughout the diurnal cycle. Geostationary imagery has been collected with sufficient resolution and quality for severe storm research for over 25 years over the Americas, serving as a critical and unique dataset for deriving severe storm climatologies.

Of the three primary severe convective storm hazards, hail, tornadoes, and straight-line winds, hail is responsible for the majority of damage, resulting in at least \$10 billion in insured losses each year across the globe. Features such as anvil clouds and overshooting cloud tops are ubiquitous components of deep convection, but only a small fraction of storms with these features produce severe hail. One reason for this is that storm mode (supercell, squall line, MCS, disorganized multicell, etc.) and weather hazards generated by a storm are modulated by environmental forcing for the convection. Seemingly intense storms with cold cloud tops observed by satellites will not generate hail if they are in an unfavorable environment. Conversely, hailstorms do not occur everywhere with favorable environments depicted by models. This suggests that severe storm detection and climatologies could be optimized through a combination of automated satellite-based feature detection and environmental parameters derived from reanalyses.

An additional complexity is that the exact locations impacted by severe weather and time of event occurrence are not well known throughout much of the world, leading to uncertainty in quantifying how well severe storms can be detected. Severe weather reporting is also biased by population density, and events in rural areas or at night are under-reported. Therefore, developing an understanding of satellite-observed cloud top properties occurring at the time of severe weather is challenging. Over the U.S., Europe, and other regions with weather radar networks, hail size can be estimated via the Maximum Expected Size of Hail (MESH) product that can be used as a proxy for spotter reports and to develop/verify automated satellite-based hailstorm detection models.

This project, supported by the NASA Applied Sciences Disasters program, seeks to combine satellite observations and reanalyses using Machine Learning to derive hail climatologies and assess hailstorm risk across the world. We demonstrate this capability over the U.S. using data from 2013-2017 where NEXRAD MESH, GOES satellite, and MERRA-2 and ERA5 data are available.

### Key Questions Addressed By This Research

How do GOES and reanalysis parameters vary as a function of hail size derived from NEXRAD MESH, and for cells with severe weather reports or warnings across the U.S.?

How well can a machine learning model trained with reanalysis-only, satellite-only, and a combination of reanalysis+satellite perform with differentiating severe from non-severe hailstorms defined by NEXRAD MESH? Does use of MERRA-2 vs ERA5 reanalysis impact the results?

Are the spatio-temporal characteristics of a filtered satellite+reanalysis hailstorm climatology supported by climatologies derived from MESH, hail reports, and passive microwave imagers?

## Datasets Analyzed

GOES-13 4-km gridded 10.7  $\mu\text{m}$  brightness temperature at up to 5-minute intervals from Jan-Dec 2013-2017 across CONUS from 65° to 115° West longitude. GOES-16 2-km gridded data at 15-minute intervals from April-Sept 2017

GOES-derived products (see Table below) using NASA Langley automated algorithms (Khlopenkov et al., Cooney et al. 2021) designed to detect and characterize deep convection at the GOES pixel scale

Gridded NEXRAD WSR-88D Radar (GridRad; Homeyer and Bowman 2017 and references therein), 75<sup>th</sup> and 95<sup>th</sup> percentile Maximum Expected Size of Hail (MESH75 and MESH95, Murillo and Homeyer 2019, 2021) at hourly intervals from 2013-2017

Hailstorm detections from TRMM (Jan-March 2013) and GPM (Mar 2014-Dec 2017) Microwave Imagers, and AMSR2 (2013-2017) based on methods described by Bang and Cecil (2019, 2021)

Convective environment parameters (see Table Below) derived from the MERRA-2 and ERA-5 reanalyses

Severe weather reports from the NOAA Storm Prediction Center Database (<https://www.spc.noaa.gov/climo/online/>)

National Weather Service Severe Weather Warnings from the Iowa Environmental Mesonet (<https://mesonet.agron.iastate.edu/vtec/search.php>)

## Satellite and Reanalysis Parameters Analyzed

GOES Parameters	MERRA-2 and ERA5 Reanalysis Parameters
Cold Spot - Tropopause BT	Surface-Based CAPE
Cold Spot - Anvil BT	Mixed Layer CAPE from 0-500 m and 0-1000 m parcels
Overshooting Top (OT) Probability	Most Unstable CAPE
Overshooting Top (OT) Area	Surface-Based CIN
Peak Cloud Height	Mixed Layer CIN from 0-500 m and 0-1000 m parcels
Area of Cloud < 225 K Surrounding Cold Spot	Most Unstable CIN
Mean Anvil Height Surrounding Cold Spot	Surface-Based LCL
	Mixed-Layer LCL from 0-500 m parcels
	Freezing Level
	0-1-km and 0-6 km Vertical Wind Shear
	500-hPa Air Temperature
	700-500-hPa Lapse Rate
	Tropopause Height
	Significant Hail Parameter (SHIP)
	0-1 km and 0-3 km Storm Relative Helicity
	Thickness of the Hail Growth Zone (-10° to -30° C)

## Analysis Methods

Identify spatially-filtered local MESH95 maxima (spacing  $\geq 30$  km) that serve as a proxy for convective cells

Extract parallax-corrected GOES convection characterization products within 7x7 GOES-13 pixels and within 7.5 minutes of the hourly MESH95 cell locations. Record the most extreme value for each parameter within this 7x7 pixel window, only when an Embedded Cold Spot (see right-bottom panel) is co-located with a MESH cell

Temporally interpolate MERRA-2 and ERA5 reanalysis convection environment parameters to the time of the GOES image. Record the most extreme value within a 1.8° x 1.5° radius (3x3 (7x6) MERRA-2 (ERA5) grid points) and combine with the GOES-derived products. A total of 266,517 data records were derived across the 5-year period. A threshold of 1.15 inches was chosen to provide a near-equal balance between the severe and non-severe classes.

Use data from years 2013-2016 to train a Random Forest model to differentiate storms with MESH95  $\geq 1.15$  inch (2.9 cm) from those with smaller hail. The model is tested on data from 2017.

Develop predictive models with MERRA-2 or ERA5 reanalysis-only, GOES-only, and reanalysis+GOES inputs to assess the value of each input type. GOES-16 is used as input to the model derived from GOES-13 for April-September 2017 only.

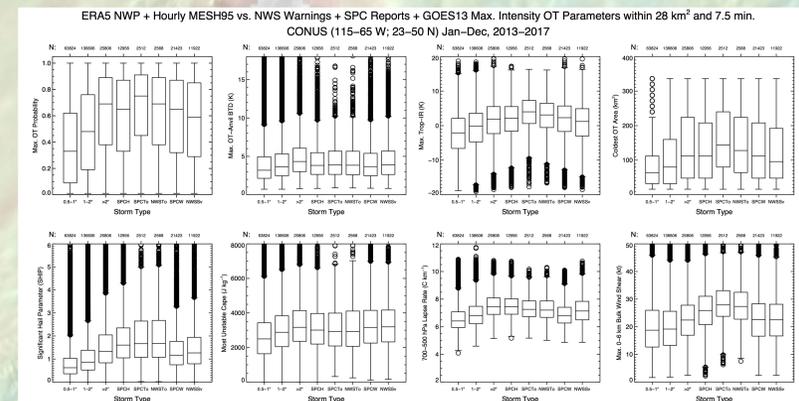
## What Is The Satellite and Reanalysis Parameter Space For Storms With Warnings, Human Spotter Reports, and Varying MESH?

Nearly all satellite and reanalysis parameters increase in intensity with increasing MESH. There is considerable overlap between the < 1 inch "non-severe" and > 1 inch "severe hail" classes. This makes automated discrimination of severe hail very challenging

For the reanalysis parameters, storms with reported hail (1+ inch) appear more intense than even the 2+ inch hailstorms defined by MESH, but this is not the case for GOES-13 parameters

Reported tornado events have the greatest median intensity for nearly all parameters

Temporal and spatial uncertainty in the GOES-13 -> MESH matching process contributes to the scatter in these distributions



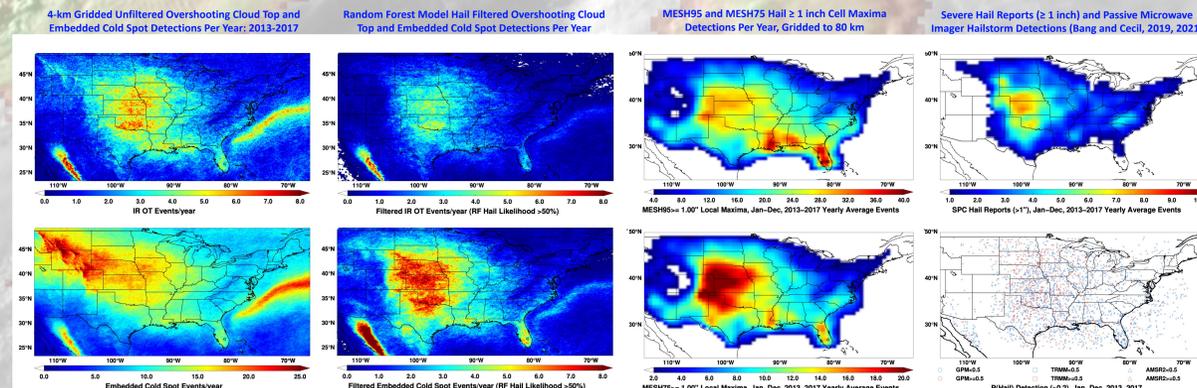
0.5-1", 1-2", and < 2" Hail Size Determined by 95<sup>th</sup> Percentile MESH  
 SPCH, SPCTO, and SPCW Hail, Tornado, and Wind Reports from the NOAA Storm Prediction Center Database  
 NWSTo and NWSSV Tornado and Severe Thunderstorm Warnings Issued By the NOAA National Weather Service Center Database

## GOES, NEXRAD, and Passive Microwave Hailstorm Detection Maps: 2013-2017

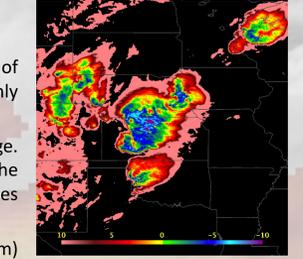
A 5-year database of overshooting cloud top (OT) detections and embedded infrared cold spots (1st column) were filtered by a Hail Probability  $\geq 0.5$  from the Random Forest model (2nd column)

The filtering process greatly reduces event counts over the Gulf Stream, Gulf of Mexico and Eastern U.S. while preserving maxima over the Great Plains and Sierra Madre where severe hail from NEXRAD MESH75 ad MESH95 (3<sup>rd</sup> column), hail reports (4<sup>th</sup> column, top), and GPM/TRMM/AMSR2 passive microwave hail detections (4<sup>th</sup> column, bottom) most often occurred

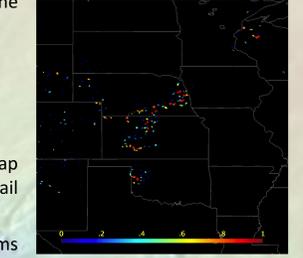
Differences between frequency of MESH cell (20-40+/year), IR OT detections where hail determined to be likely (5/year), and report counts attributed to differences in temporal sampling frequency and spatial resolution of the GOES data vs. other data grids. Normalization procedures for the GOES counts are being developed.



Tropopause-Relative GOES-13 IR Temperature 16 May 2017 at 2330 UTC



Embedded Cold Spot Detection Colored By Overshooting Cloud Top Probability



## Hailstorm Model Validation

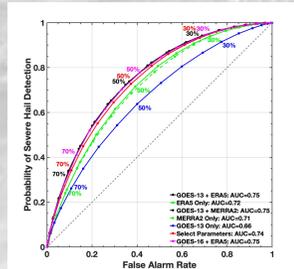
GOES + reanalysis data improves detection of severe hail from MESH95 over the use of reanalysis or GOES alone. POD increases by 10+% over GOES-alone

ERA5 provides minimal improvement in accuracy over MERRA-2

The increased spatial resolution of GOES-16 better depicts the most intense updrafts and severe storms, but does not provide an increase in detection skill over GOES-13

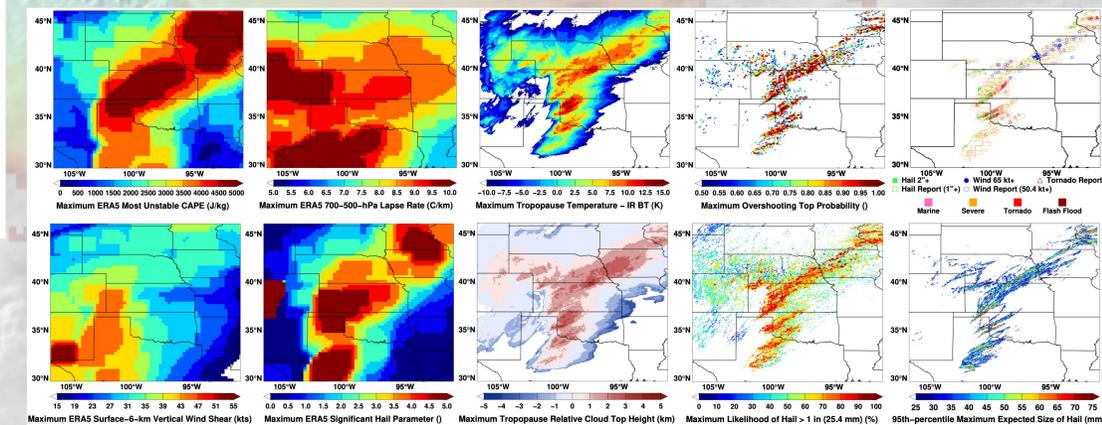
MESH75 and MESH95 increase as a function of GOES-13 severe hail probability, indicating that greater satellite-observed intensity along with a more favorable environment results in a storm more likely to generate severe hail

The dynamic range of MESH75 is lower than MESH95 so discriminating between severe and non-severe hail based on MESH75 is more challenging



## A Case Study Demonstrating The GOES-13 + ERA5 Hailstorm Detection Model

1630 UTC 16 May to 0600 UTC 17 May 2017



## Key Takeaways

This presentation demonstrates that potentially severe hail producing storms identified by NEXRAD can also be detected with relatively high accuracy using a combination of GOES satellite-derived cloud top characteristics and reanalysis environmental parameters using a Random Forest machine learning model

Significant overlap in parameter spaces between non-severe and severe hailstorms complicates discrimination of severe hailstorms

The combination of satellite + reanalysis data results in a more accurate model than reanalysis or satellite alone, increase from ~62 to 72% POD and reduced FAR. Use of ERA5 provided minimal improvement over MERRA-2

Spatial patterns in maps of GOES OT detections from likely hailstorms are supported by patterns depicted by MESH75, hail reports, and passive microwave hail detections, though the agreement is far from perfect

Our model intends to contribute to hailstorm risk assessment anywhere and at any hour across the world. Long-term GEO satellite data records input into the model will enable hailstorm risk assessments at a spatio-temporal resolution not possible from other datasets.

High resolution risk assessments are very important to the (re)insurance industry. NASA LaRC and MSFC are currently partnered with Willis Towers Watson to pioneer the use of satellite data for development of reinsurance Catastrophe Models.