

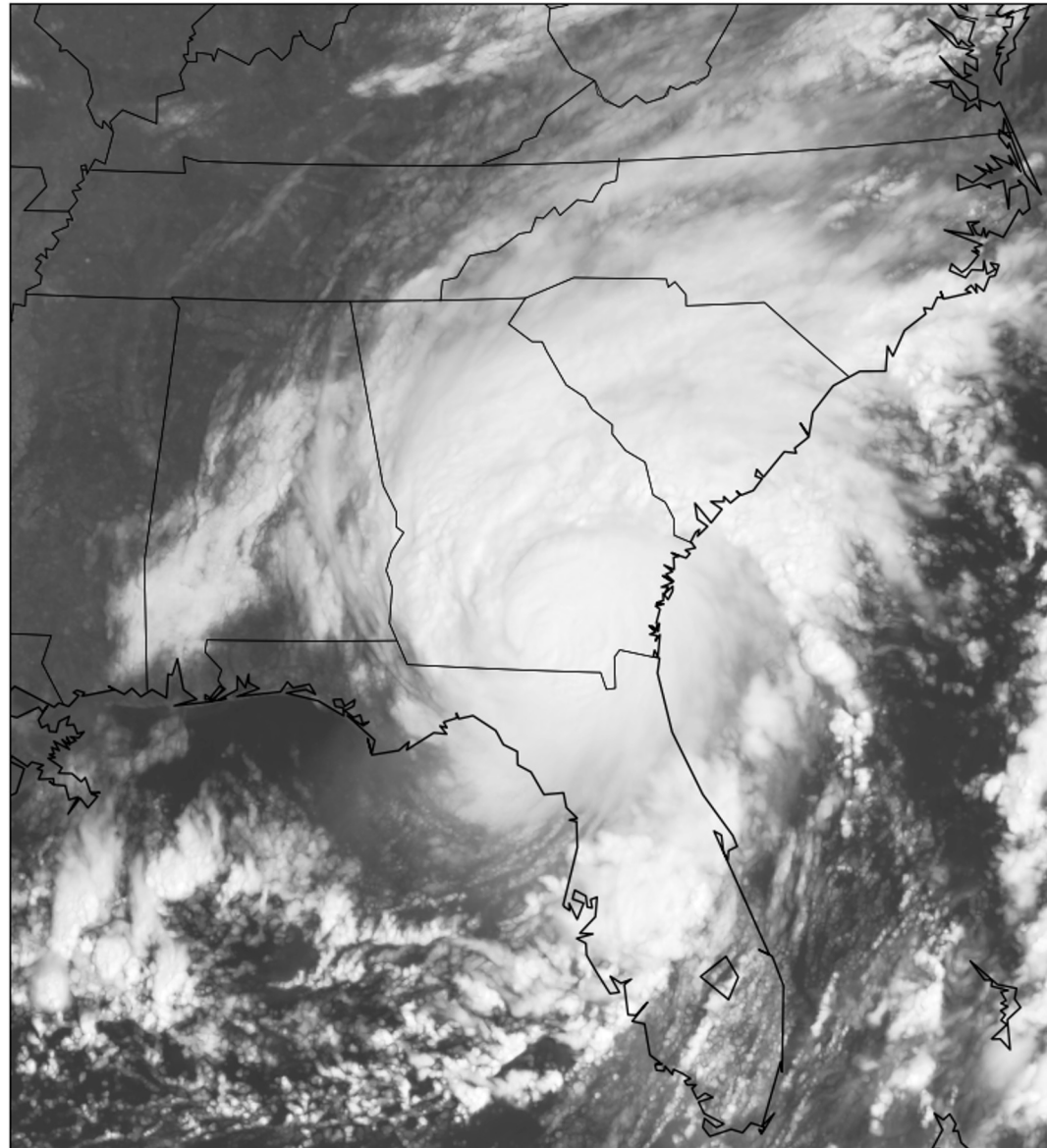
# Verifying Cloud Forecasts with Satellite Brightness Temperatures

Sarah M. Griffin and Jason A. Otkin

Cooperative Institute for Meteorological Satellite Studies, University of Wisconsin-Madison, Madison, WI



# What is a Model Cloud?

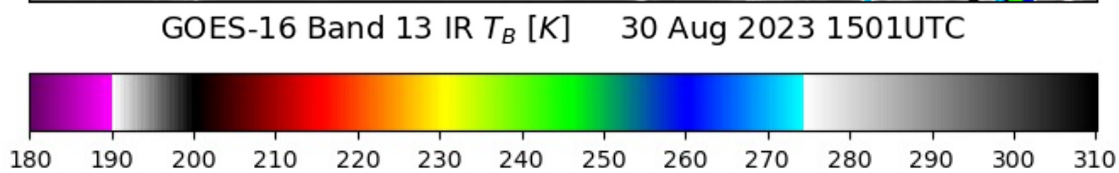
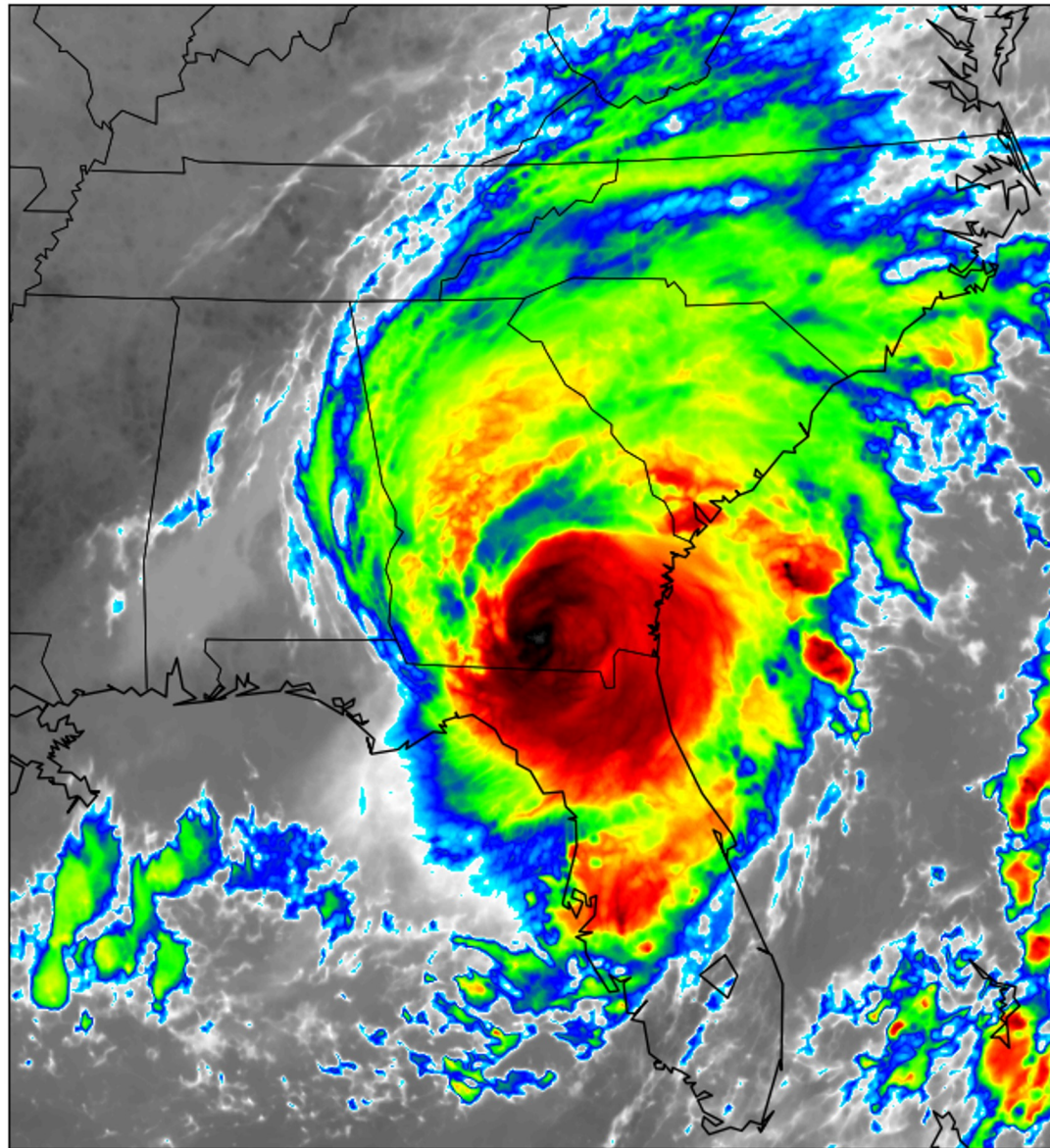


GOES-16 Band 2 Reflectance 30 Aug 2023 1501UTC

Based on visible imagery, it is easy to see what is considered cloudy.

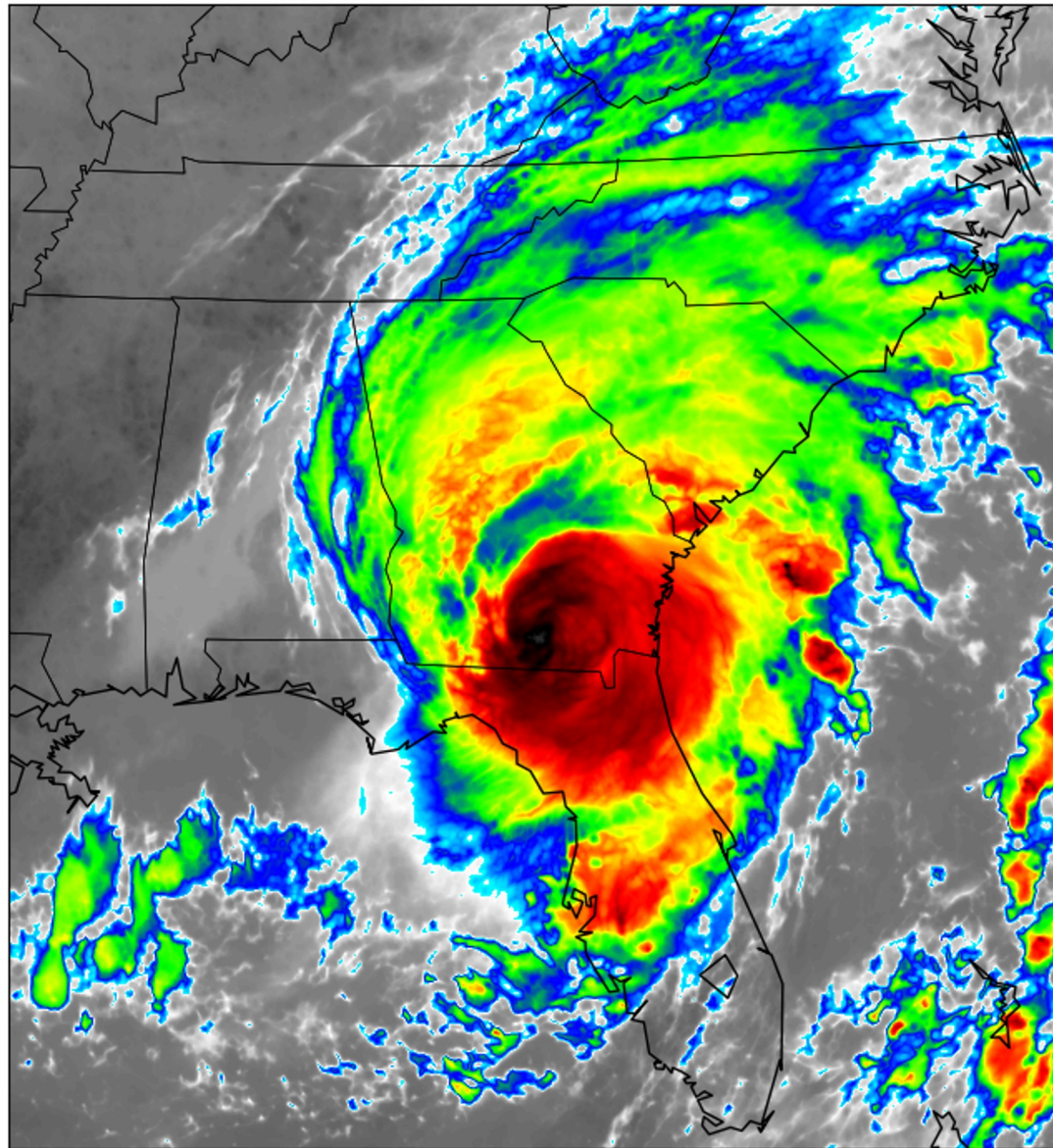
However, visible images are only available during the daytime and are hard to simulate.

# What is a Model Cloud?

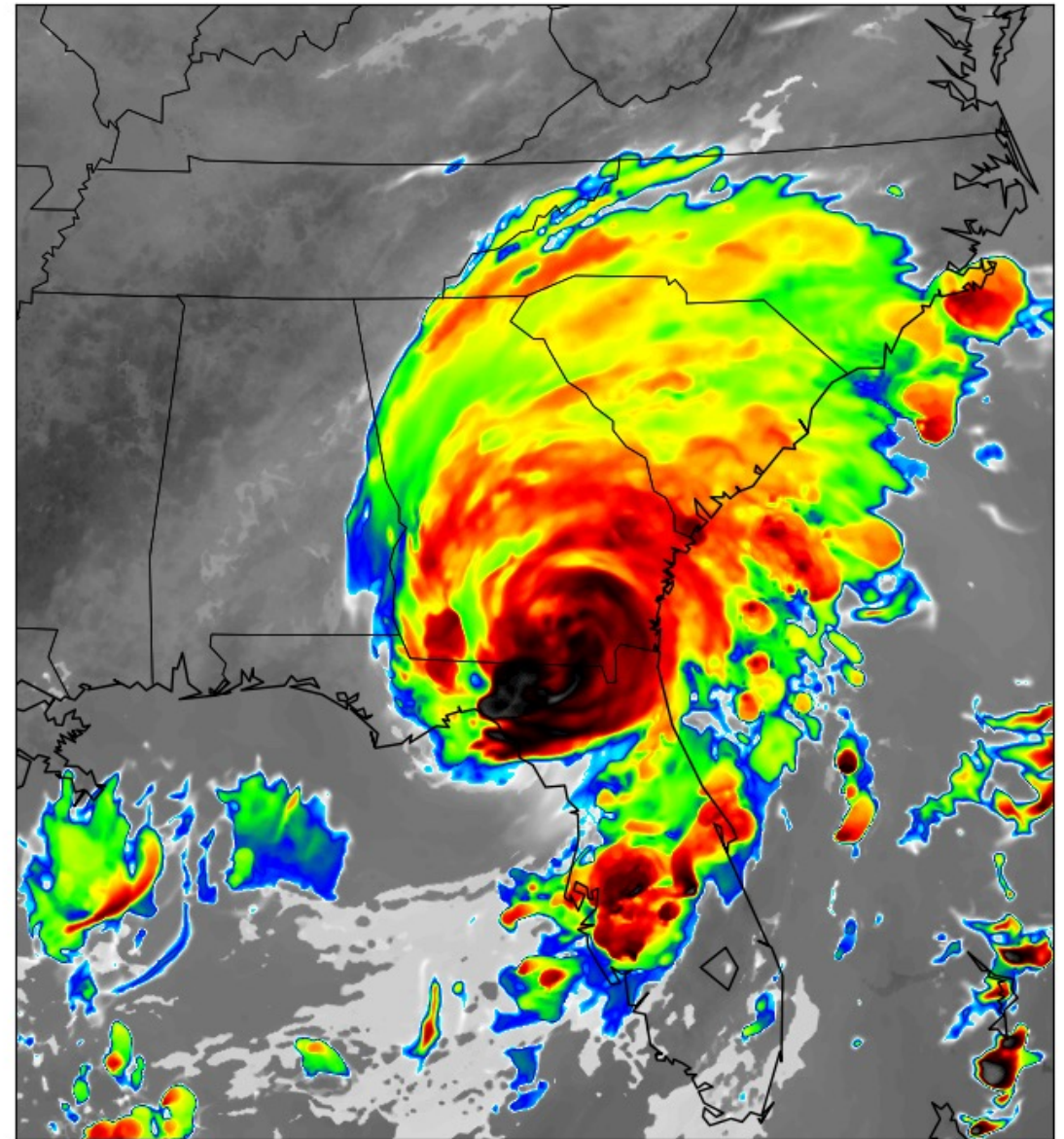
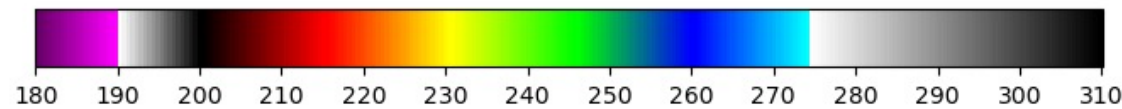




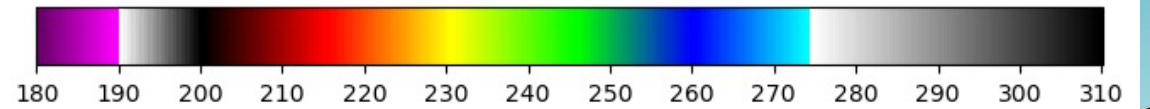
# What is a Model Cloud?



GOES-16 Band 13 IR  $T_B$  [K] 30 Aug 2023 1501UTC

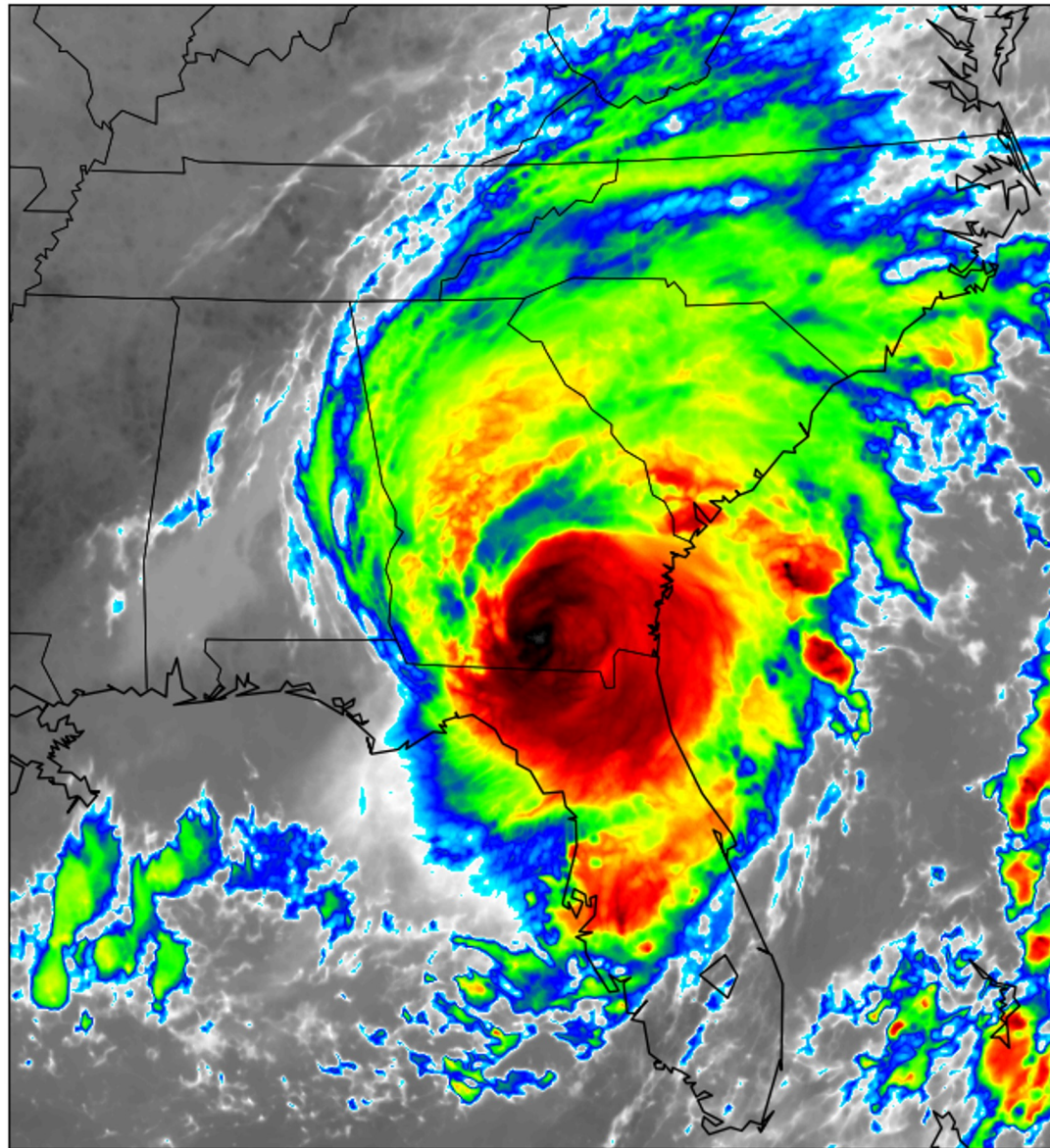


HRRR IR Window  $T_B$  [K] 30 Aug 2023 1300UTC F0200

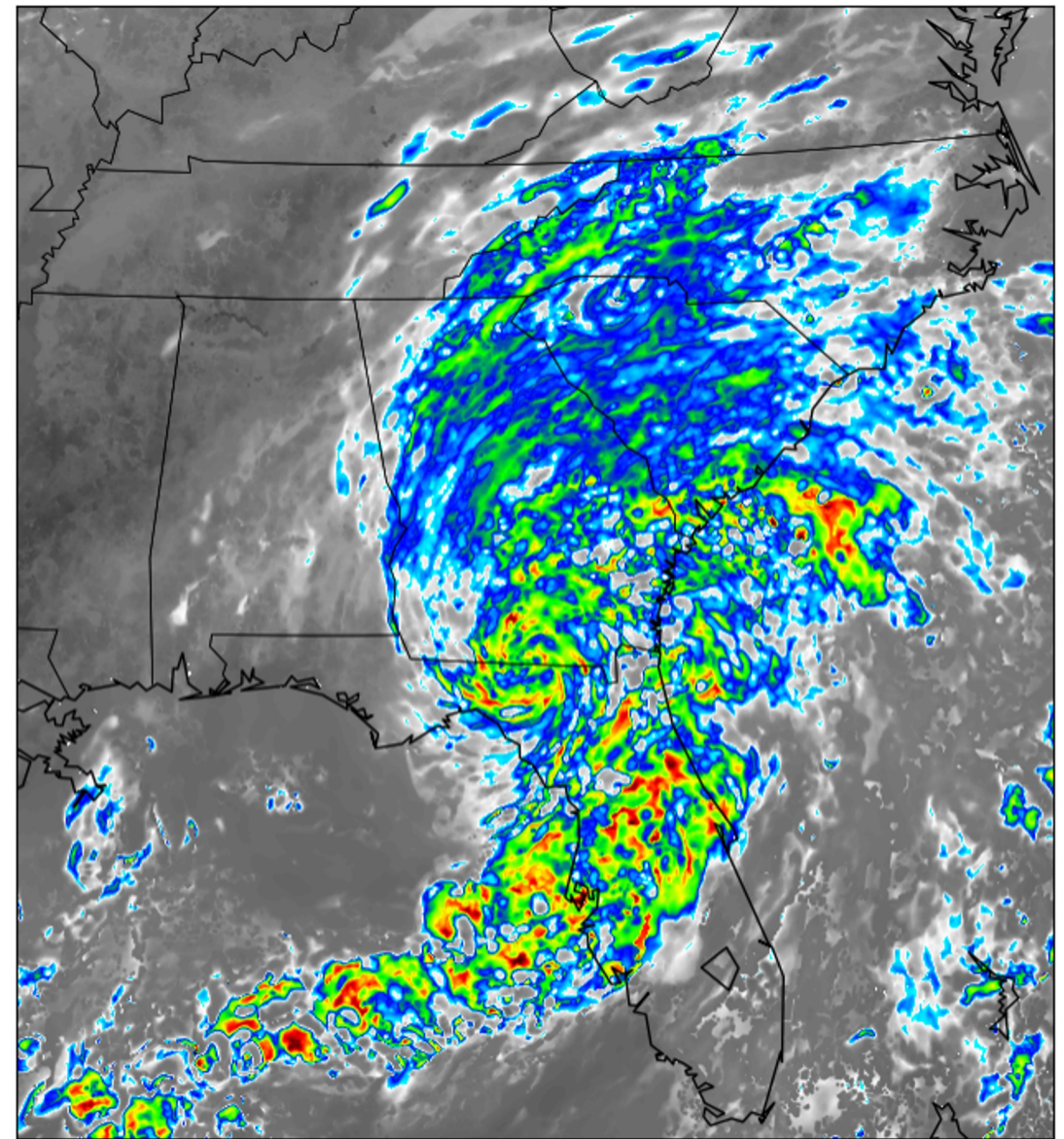
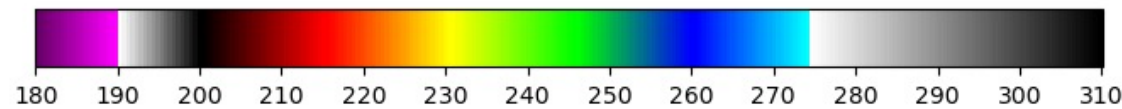




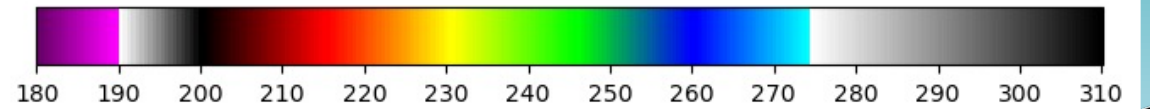
# What is a Model Cloud?



GOES-16 Band 13 IR  $T_B$  [K] 30 Aug 2023 1501UTC



RRFS Band 13 IR  $T_B$  [K] 30 Aug 2023 1300UTC F02



# Creating a Model Cloud

Many different parameters in forecast models.

Microphysics Scheme

Planetary Boundary Layer

Land Surface Model

Surface Layer

Initial Conditions

Using different schemes for the same parameter results in different answers.

How do the different schemes for these parameters impact the simulated brightness temperatures (BTs)?



# Simulated Brightness Temperature parameters

Name	Microphysics Scheme	Planetary Boundary Layer Scheme	Surface Layer	Land Surface Model	Initial and Lateral Boundary Conditions
<b>Control</b>	Thompson	MYNN	GFS	Noah	NAM
<b>MP-NSSL</b>	National Severe Storms Laboratory	MYNN	GFS	Noah	NAM
<b>PBL-SH</b>	Thompson	Shin-Hong	GFS	Noah	NAM
<b>PBL-EDMF</b>	Thompson	EDMF	GFS	Noah	NAM
<b>LSM-RUC_SFC-GFS</b>	Thompson	MYNN	GFS	RUC	NAM
<b>LSM-RUC_SFC-MYNN</b>	Thompson	MYNN	MYNN	RUC	NAM

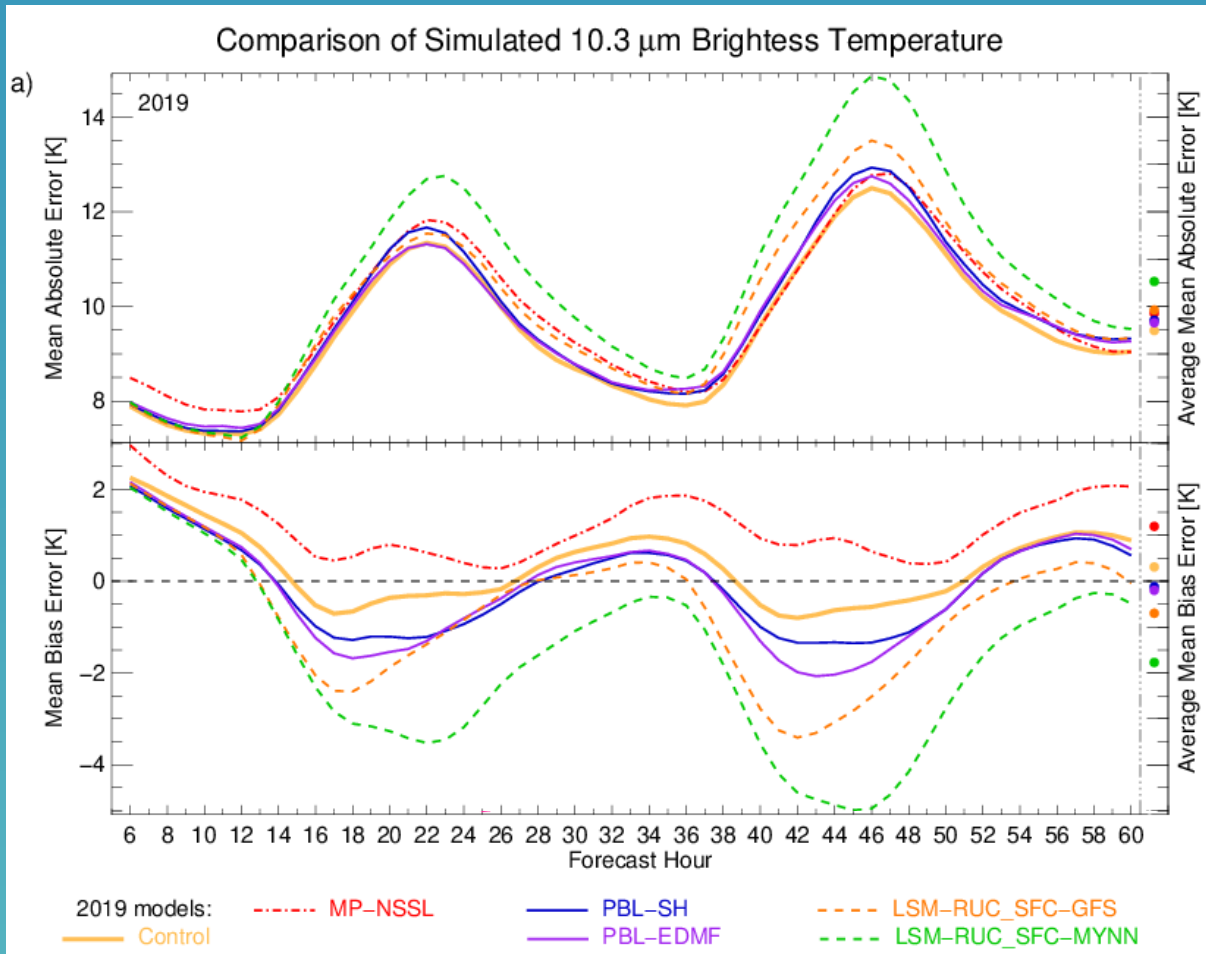
2019  
Hazardous  
Weather  
Testbed  
(HWT)

Name	Microphysics Scheme	Planetary Boundary Layer Scheme	Surface Layer	Land Surface Model	Initial and Lateral Boundary Conditions
<b>EMC FV3-LAM</b>	Geophysical Fluid Dynamics Laboratory	Hybrid-EDMF	GFS	Noah	GFS
<b>EMC FV3-LAMx</b>	Thompson	MYNN	GFS	Noah	GFS
<b>NSSL FV3-LAM</b>	Thompson	MYNN	MYNN	Noah	GFS

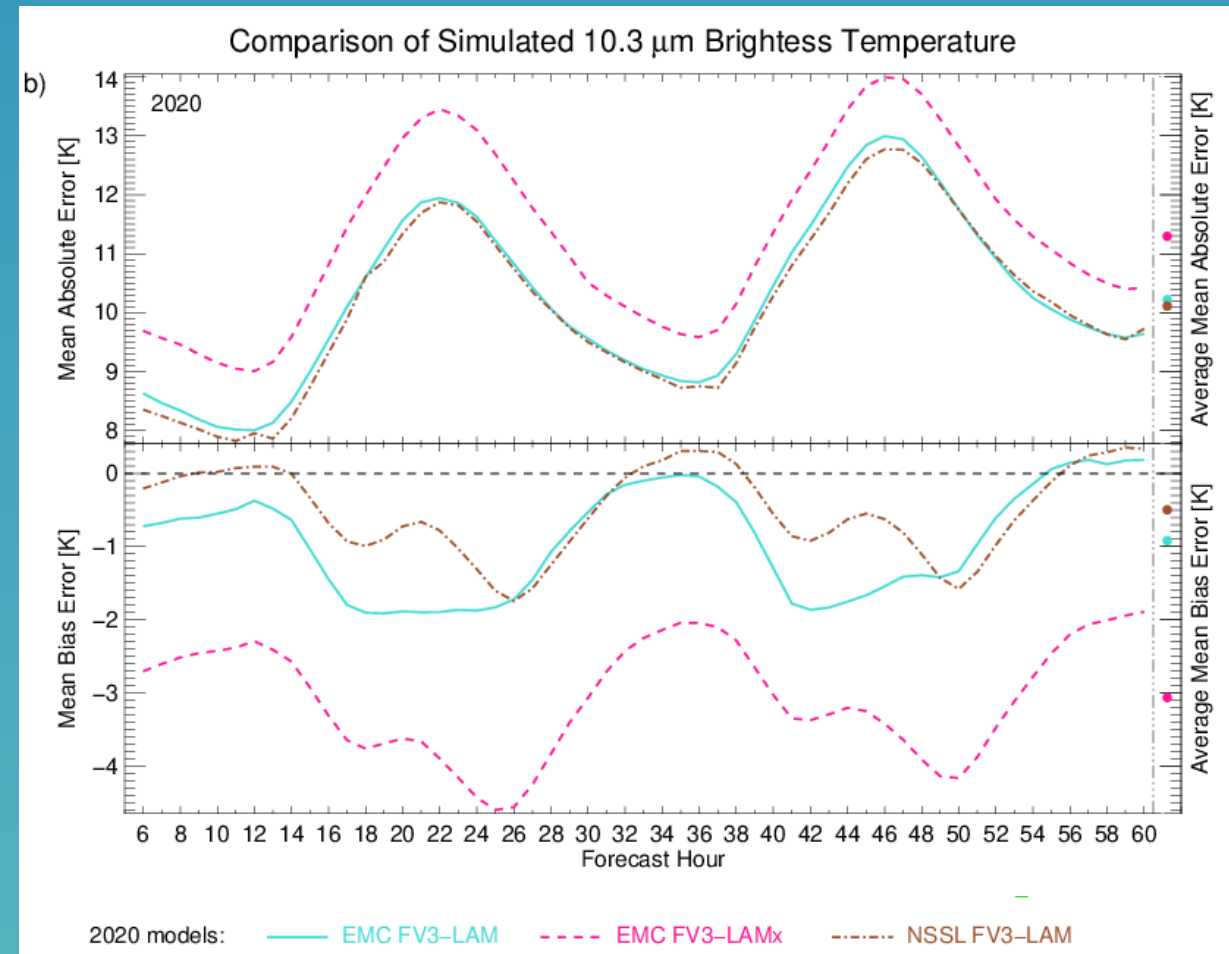
2020  
Hazardous  
Weather  
Testbed  
(HWT)

How do we assess how these different parameterizations impact the simulated BTs?

# Identifying Errors in Simulated IR BTs



NSSL microphysics scheme has a positive MBE (higher BTs) compared to Thompson.  
 RUC land surface model has more negative (lower BTs) than Noah.



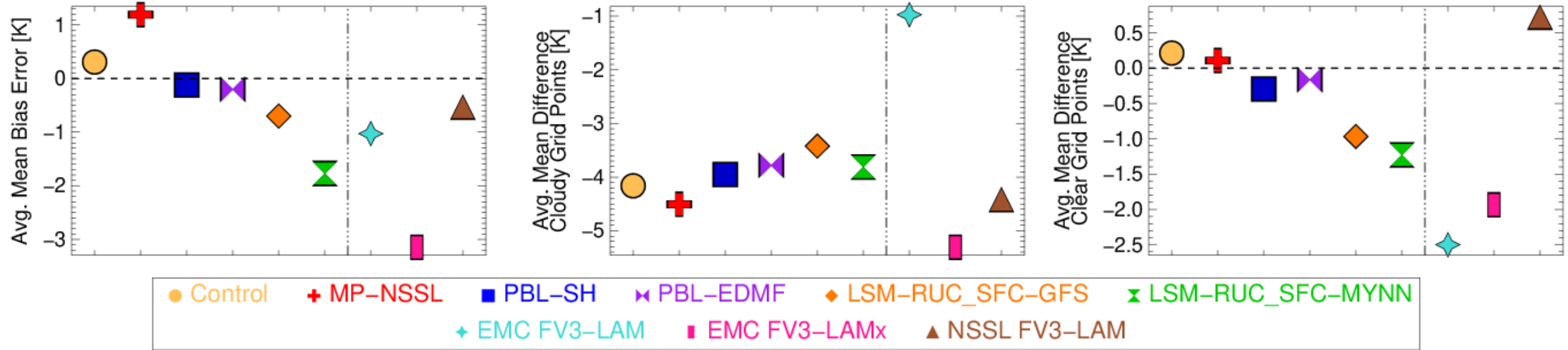
Either the GFDL microphysics scheme or the Hybrid-EDMF planetary boundary layer results in a more positive (higher BTs) compared to Thompson and MYNN.

GFS surface layer has a more negative MBE (lower BTs) compared to the MYNN.



# Identifying Errors in Simulated IR BTs

Simulated 10.3  $\mu\text{m}$  Brightness Temperature

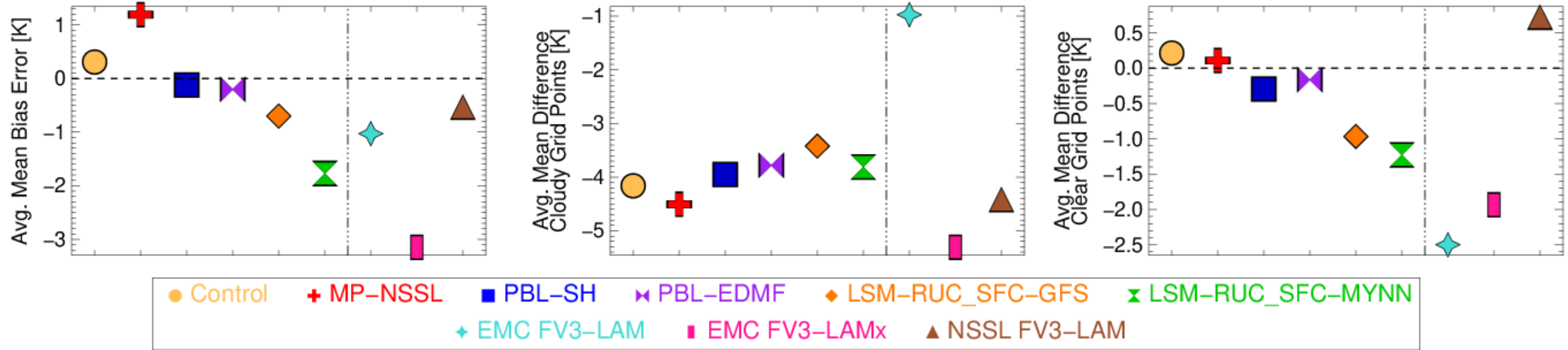


Cloudy Pixel: BT lower than 270 K.

Different number of cloudy and clear pixels, so we can only calculate the Mean Difference in the BTs.

# Identifying Errors in Simulated IR BTs

## Simulated 10.3 $\mu\text{m}$ Brightness Temperature



Cloudy Pixel: BT lower than 270 K.

Different number of cloudy and clear pixels, so we can only calculate the Mean Difference in the BTs.

All models have lower BTs for cloudy pixels.

Is this from too many cloudy pixels?

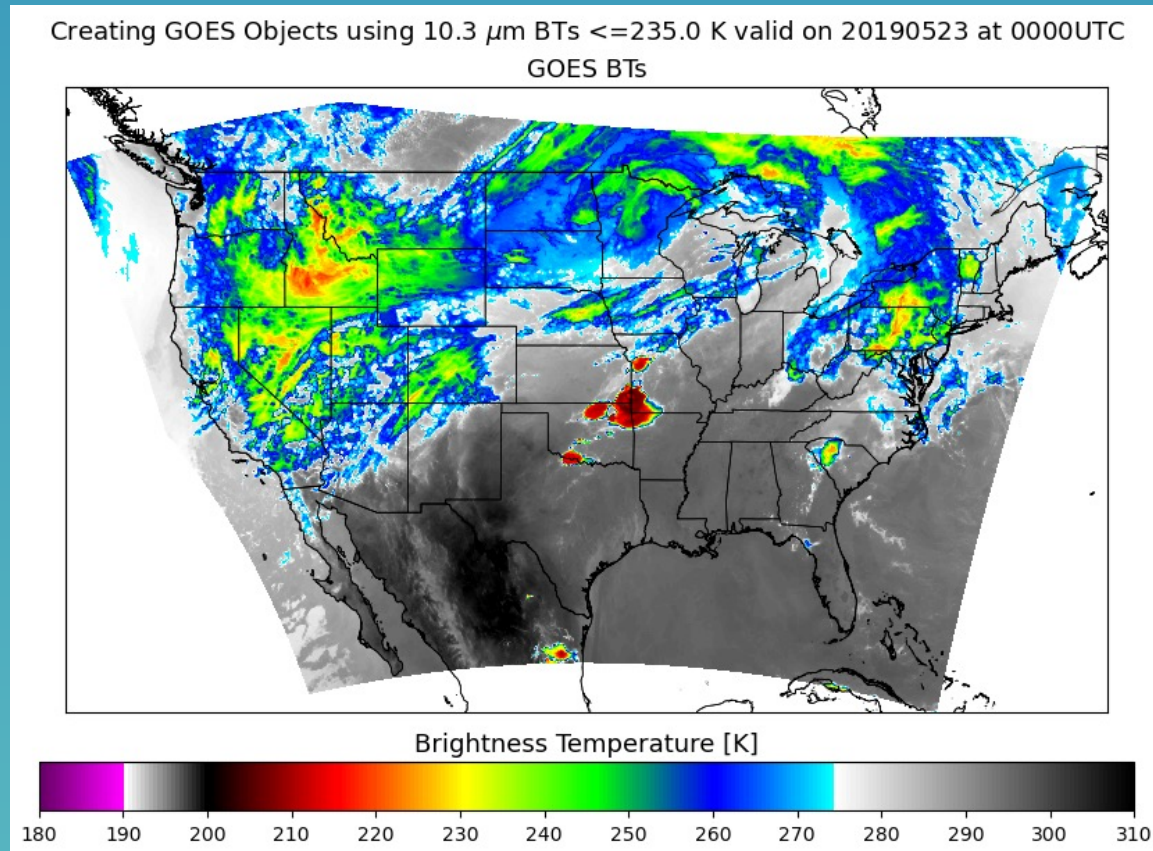
Or are the simulated BTs simply too low?

Configurations with the MYNN surface layer have simulated BTs for clear pixels that are higher than the observations.

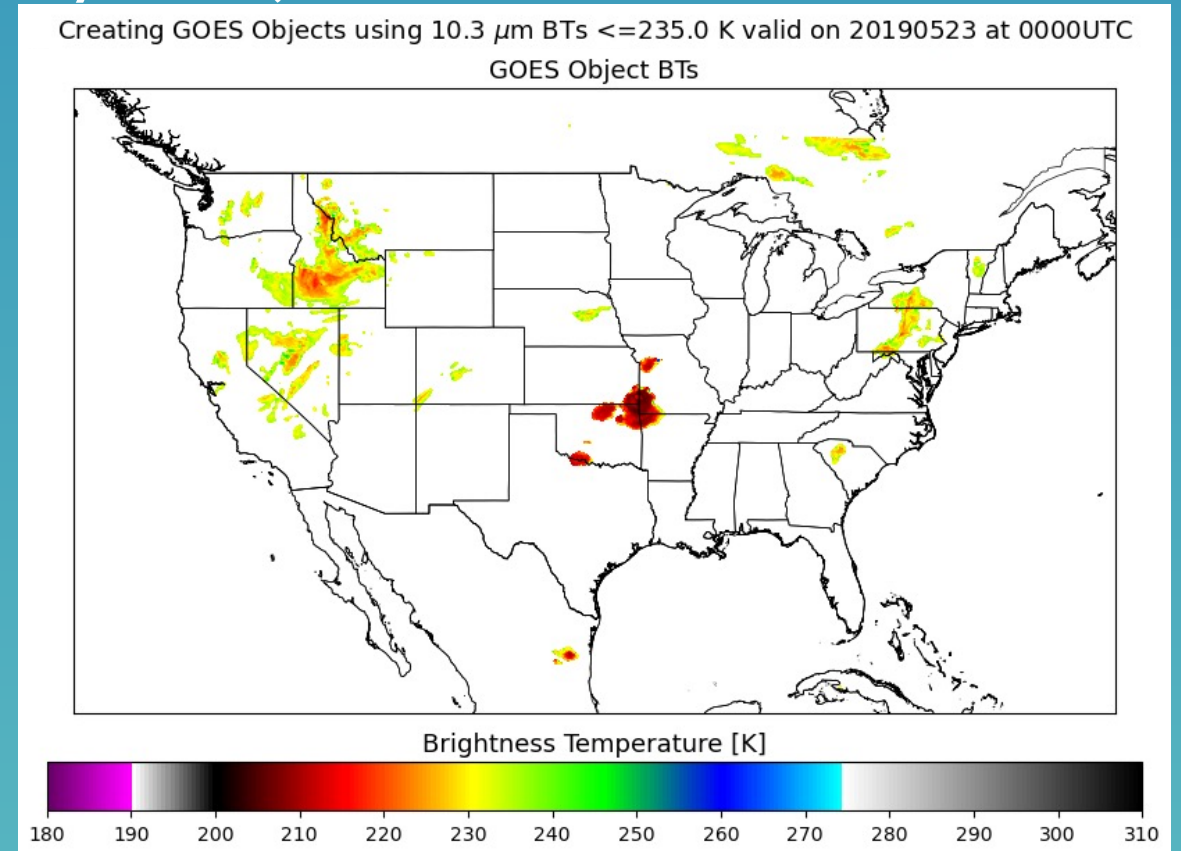


# Defining Cloud Objects in Simulated IR BTs

We use a package called MODE (Methods for Object-Based Diagnostic Evaluation) to create and analyze objects.



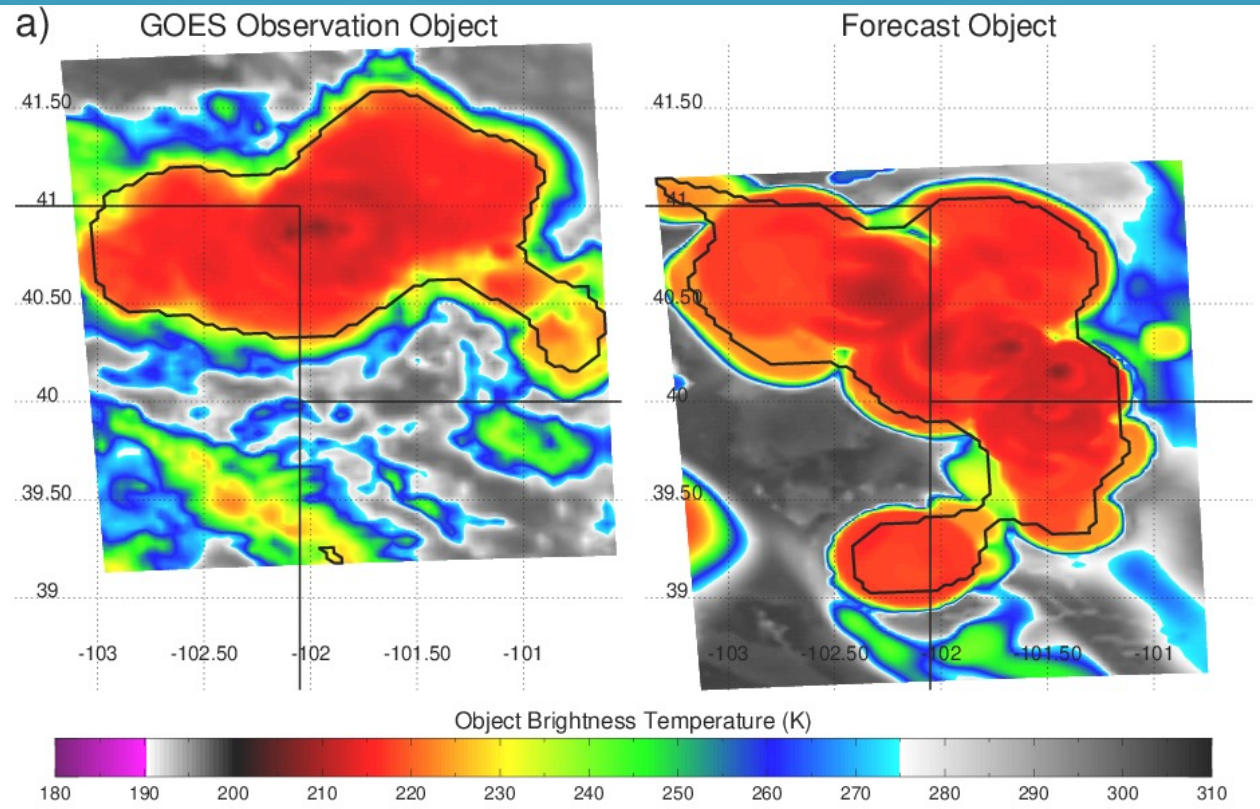
Start with BT imagery.



Finish with objects based on a given BT threshold.

MODE defines objects in both forecast and observations to assess forecast accuracy.

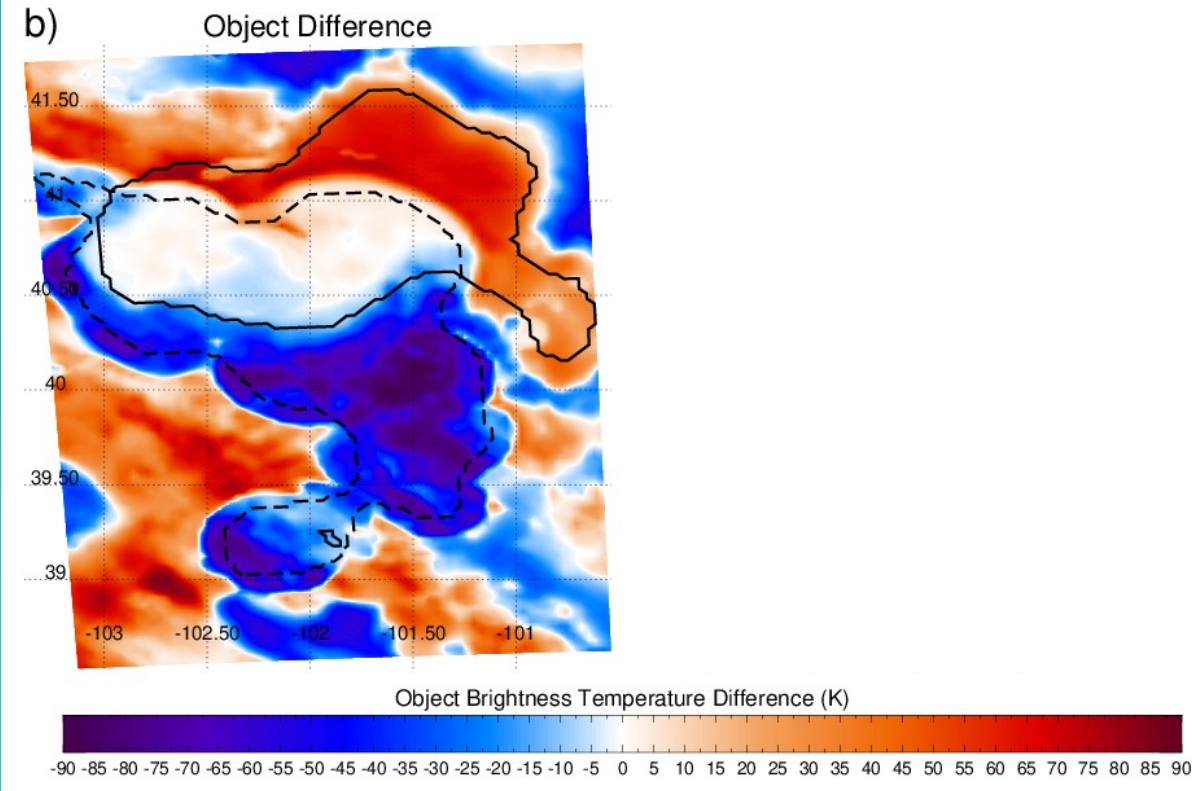
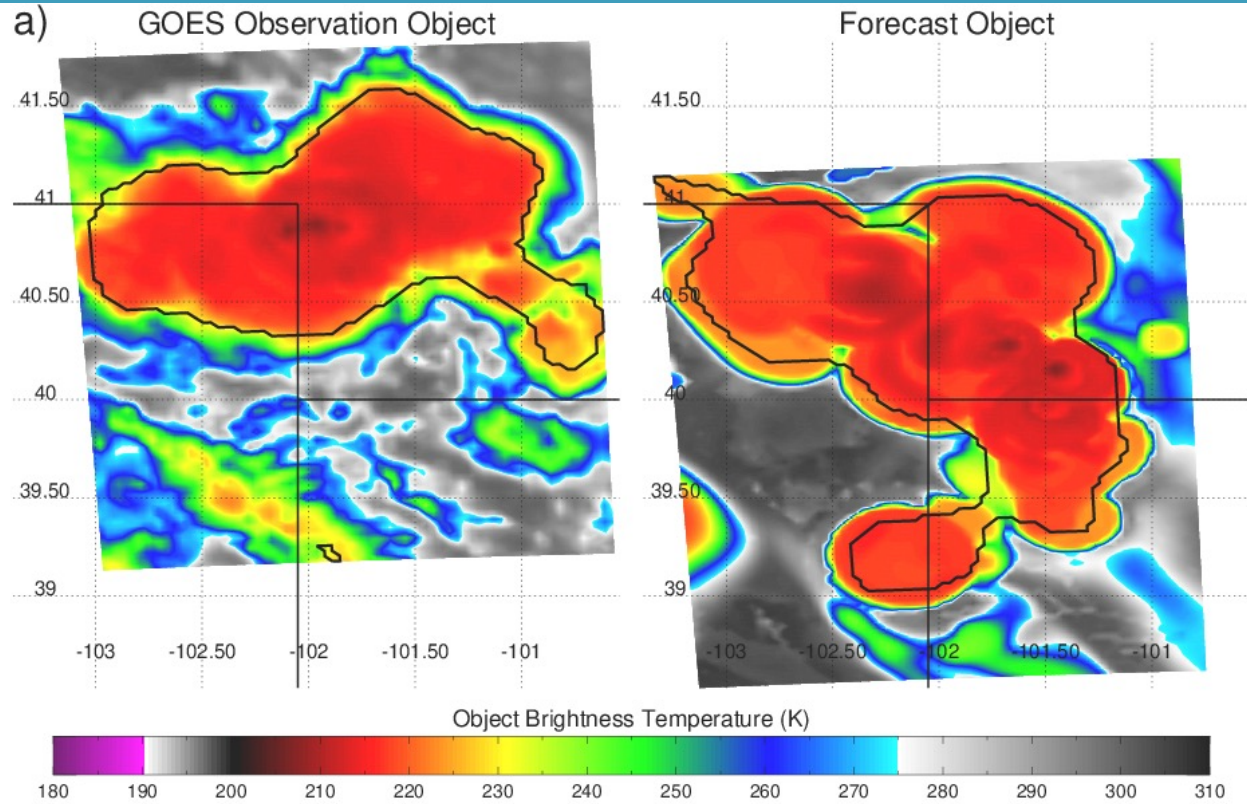
# Identifying Errors in Simulated IR BTs using Objects



Start with paired objects.



# Identifying Errors in Simulated IR BTs using Objects

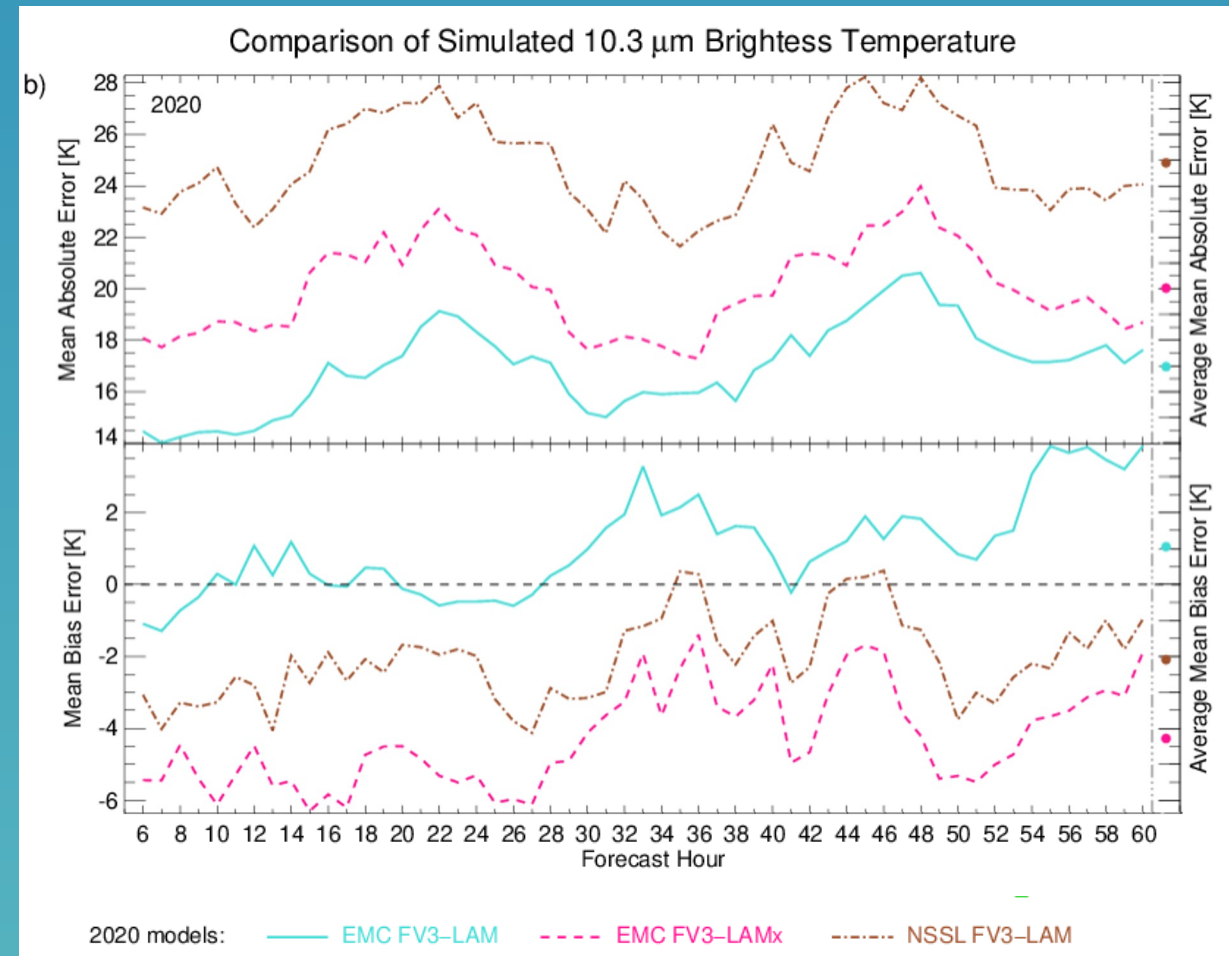
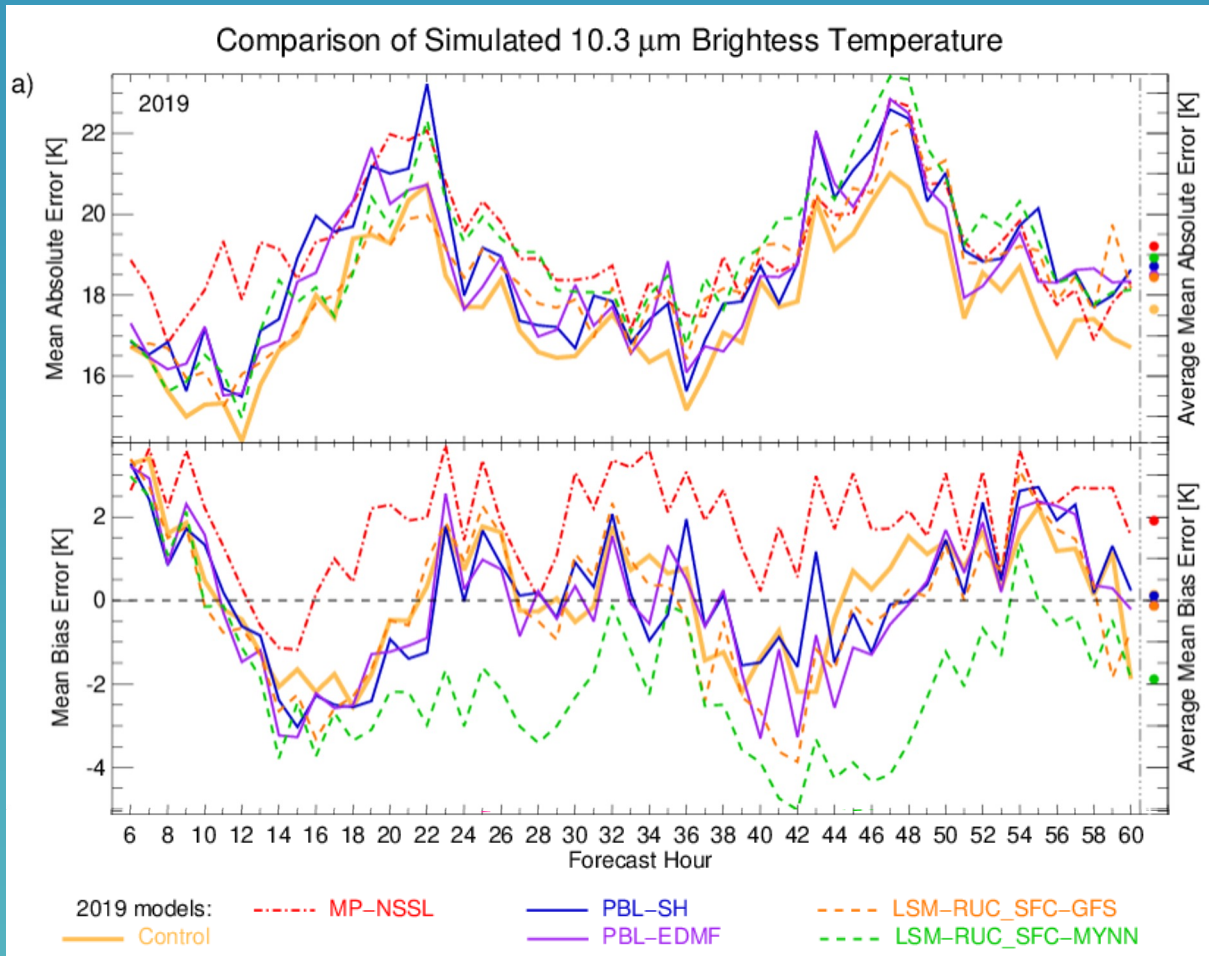


Start with paired objects.

Objects appear to be displaced.

We can use the object centers to overlap them.

# Identifying Errors in Simulated Object IR BTs



NSSL microphysics scheme has only positive MBE (higher BTs) compared to Thompson.

RUC and consistent NSSL microphysics scheme has higher BTs compared to Thompson and RUC land surface model has lower BTs than Noah.

Average MBE are closer to zero for all other models.

Using the NSSL microphysics scheme of GFS the hybrid-high EDMF boundary objects results less negative positive (higher BTs) compared to Thompson and

Either the GFDL microphysics scheme or the Hybrid-EDMF surface boundary objects results MBE (higher BTs) are comparable to the MYNN.

EMF surface boundary objects results MBE (higher BTs) are comparable to the MYNN.



# Identifying Errors in Simulated IR BTs using Objects

MODE defines objects in both forecast and observations to assess forecast accuracy. Interest scores assess how well objects are matched.

Object Pair Attribute	User-Defined Weight (%)	Description
<b>centroid_dist</b>	4 (25.0)	Distance between objects' "center of mass"
<b>boundary_dist</b>	3 (18.75)	Minimum distance between the objects
<b>convex_hull_dist</b>	1 (6.25)	Minimum distance between the polygons surrounding the objects
<b>angle_diff</b>	1 (6.25)	Orientation angle difference
<b>area_ratio</b>	4 (25.0)	Ratio of the forecast and observation objects' areas (or its reciprocal, whichever yields a lower value)
<b>int_area_ratio</b>	3 (18.75)	Ratio of the objects' intersection area to the lesser of the observation or forecast area (whichever yields a lower value)

# Identifying Errors in Simulated IR BTs using Objects

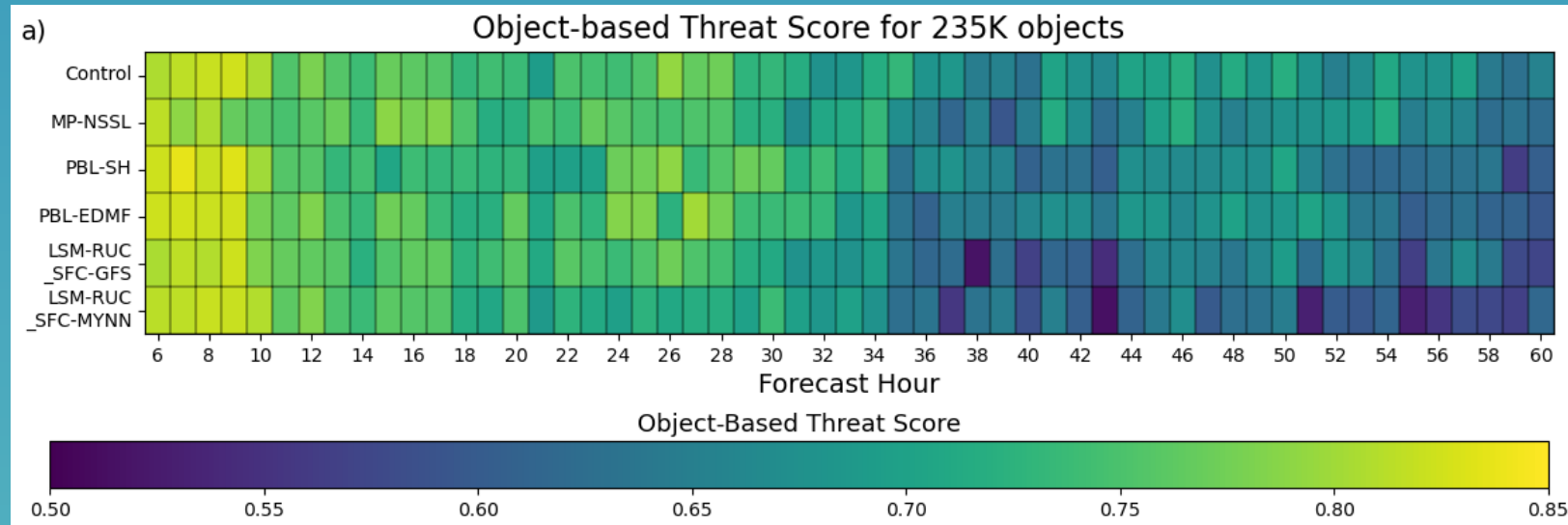
Object-based Threat Score: 
$$OTS = \frac{1}{A_f + A_o} \left[ \sum_{p=1}^P IP(a_f^p + a_o^p) \right]$$

- $A_f$  and  $A_o$  represent the total area of paired and unpaired forecast and observation objects, respectively.
- $P$  represents the number of paired forecast and observation object pairs.
- $IP$  represents the interest score between the paired forecast and observation object/cluster
- $a_f^p$  and  $a_o^p$  represent the areas of the forecast and observation objects/clusters in the pair, respectively.



# Identifying Errors in Simulated IR BTs using Objects

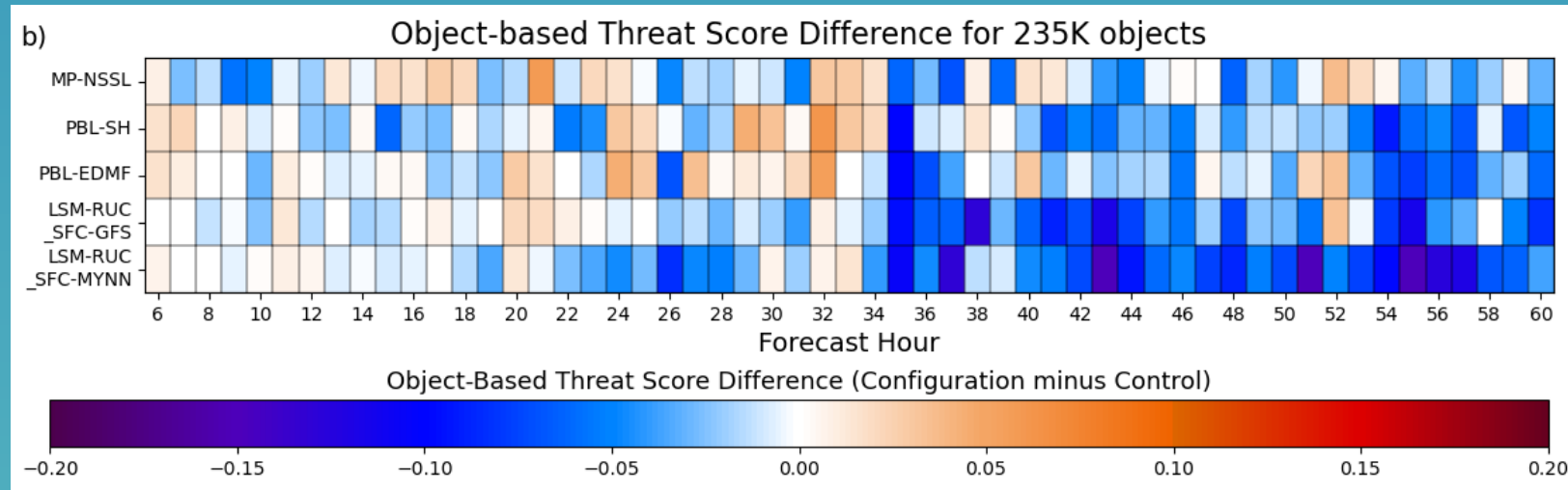
Object-based Threat Score: 
$$OTS = \frac{1}{A_f + A_o} \left[ \sum_{p=1}^P IP(a_f^p + a_o^p) \right]$$



Forecasts are more accurate earlier in the forecast cycle compared to later.

# Identifying Errors in Simulated IR BTs using Objects

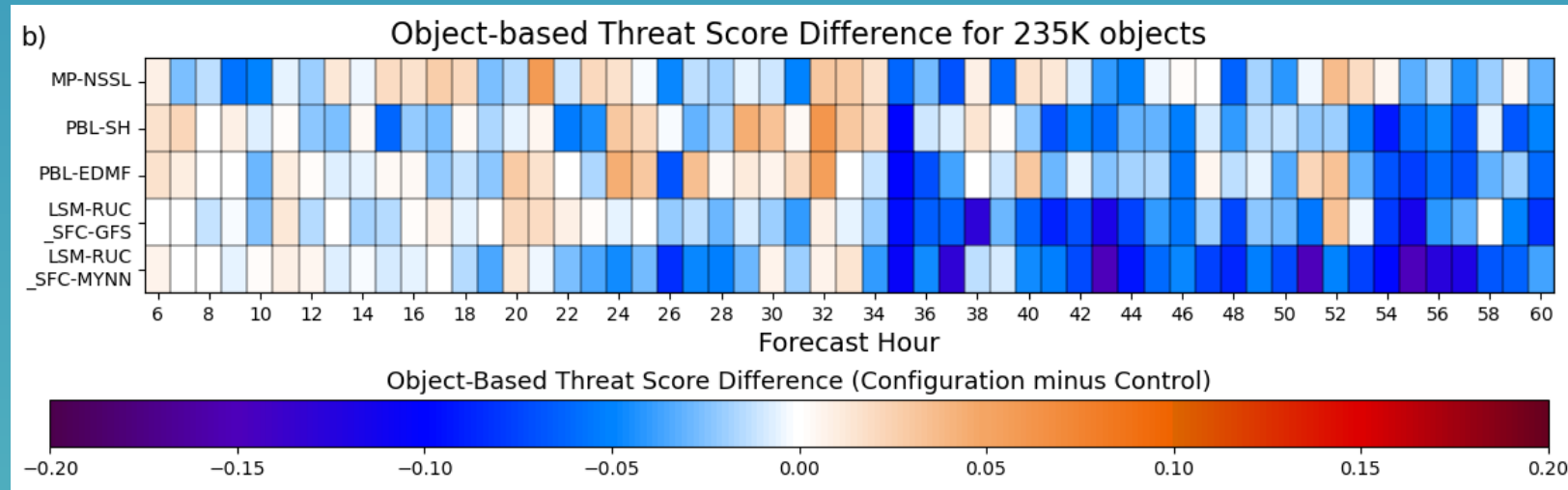
Object-based Threat Score: 
$$OTS = \frac{1}{A_f + A_o} \left[ \sum_{p=1}^P IP(a_f^p + a_o^p) \right]$$



- The Shin-Hong PBL scheme has more accurate cloud features than the MYNN for early forecast hours.
- The LSM-RUC\_SFC-MYNN forecasts have the steepest reduction in OTS as the forecast hour increases, followed by LSM\_RUC\_SFC-GFS, which indicates that the rapid decrease in accuracy is due to the RUC LSM.

# Identifying Errors in Simulated IR BTs using Objects

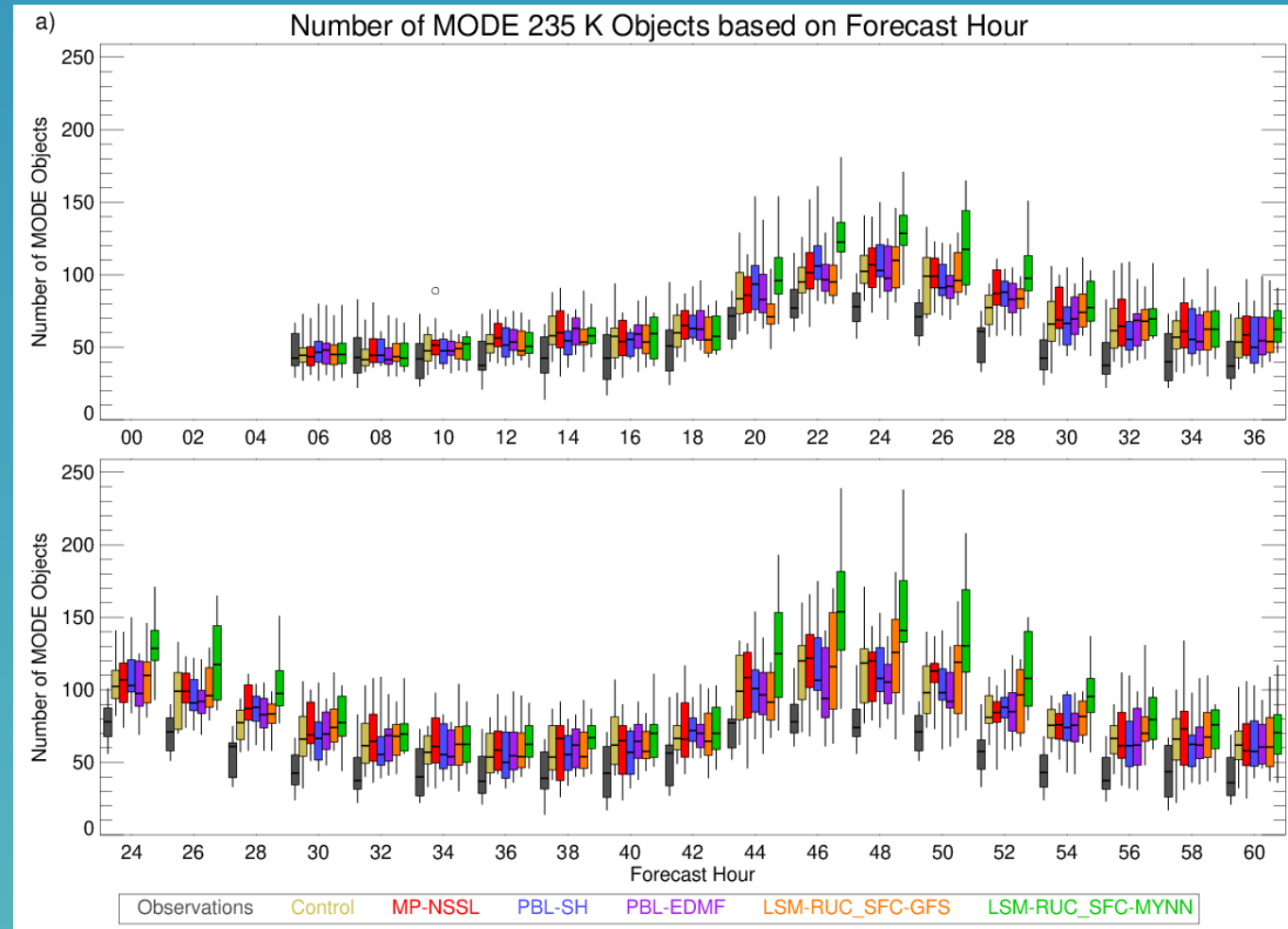
Object-based Threat Score: 
$$OTS = \frac{1}{A_f + A_o} \left[ \sum_{p=1}^P IP(a_f^p + a_o^p) \right]$$



- The Shin-Hong PBL scheme has more accurate cloud features than the MYNN for early forecast hours.
- The LSM-RUC\_SFC-MYNN forecasts have the steepest reduction in OTS as the forecast hour increases, followed by LSM\_RUC\_SFC-GFS, which indicates that the rapid decrease in accuracy is due to the RUC LSM. But Why??

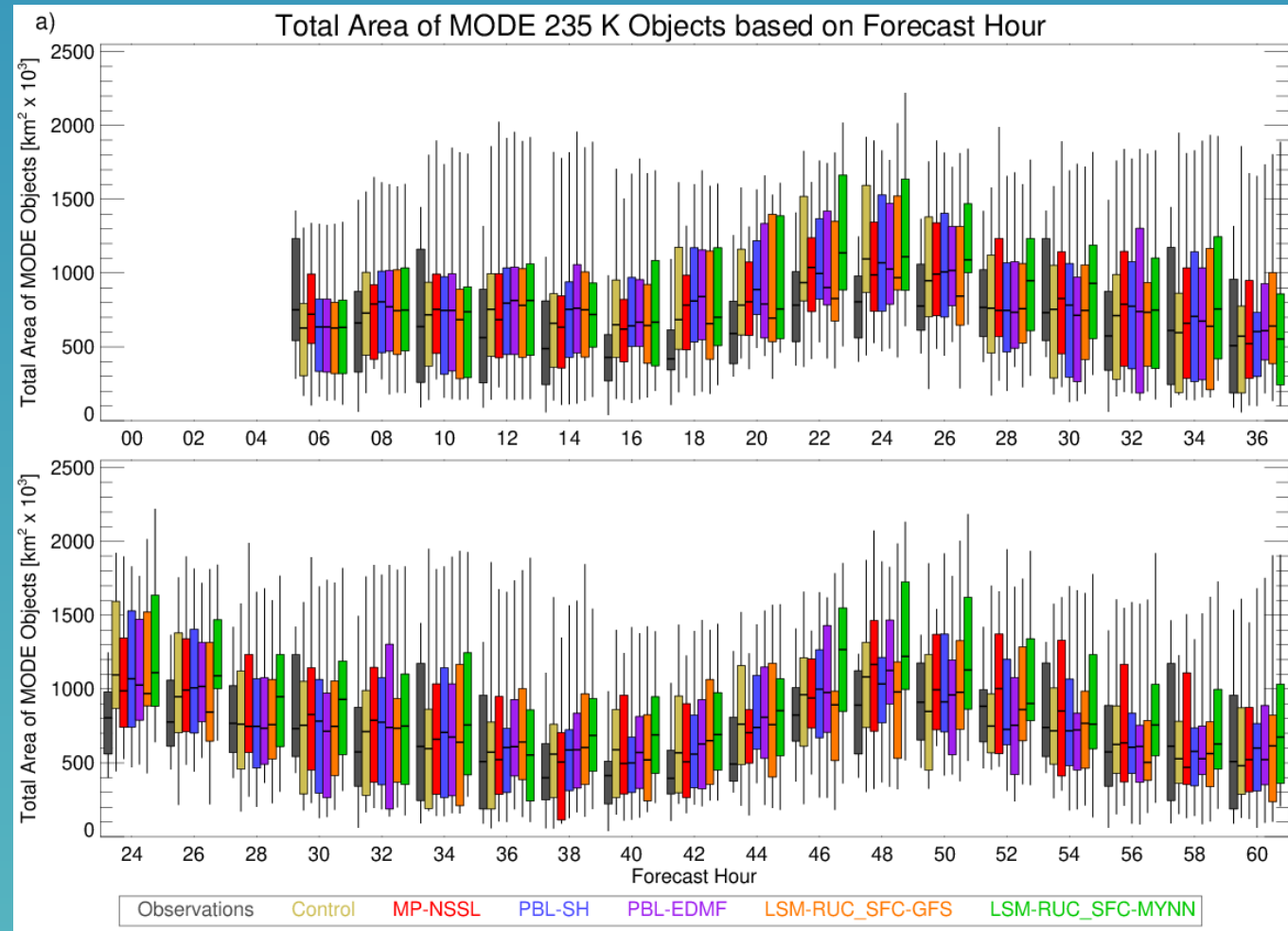


# Identifying Errors in Simulated IR BTs using Objects



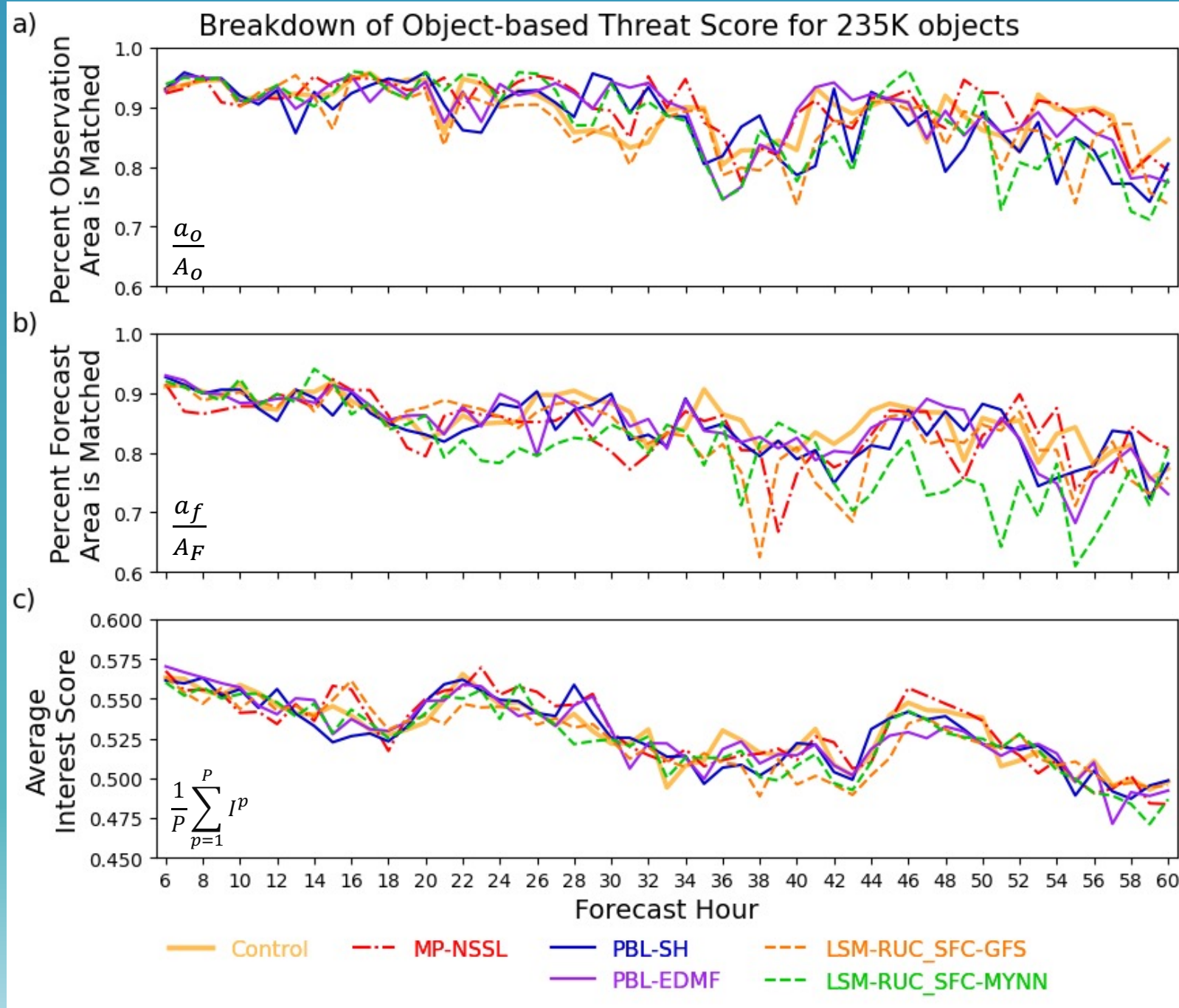
LSM-RUC\_SFC-MYNN and LSM\_RUC\_SFC-GFS produced more objects than other model set-ups or the observations, especially later in the forecast cycle.

# Identifying Errors in Simulated IR BTs using Objects



LSM-RUC\_SFC-MYNN and LSM\_RUC\_SFC-GFS produced more objects than other model set-ups or the observations, especially later in the forecast cycle. LSM-RUC\_SFC-MYNN also produces more object area than other model set-ups or the observations, especially later in the forecast cycle.

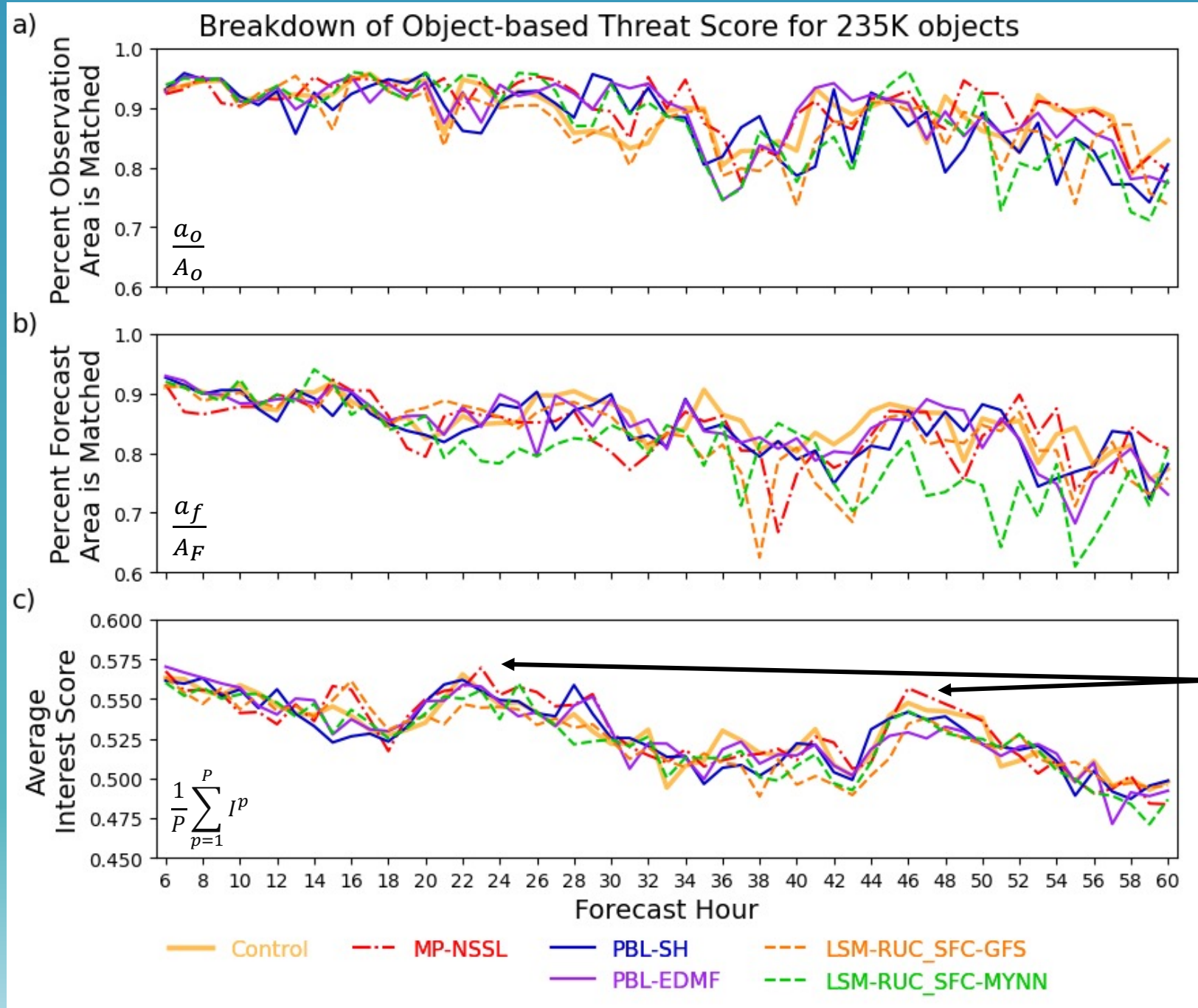
# Identifying Errors in Simulated IR BTs using Objects



LSM-RUC\_SFC-MYNN forecasts have the lowest percent of forecast area matched later in the forecast cycle.



# Identifying Errors in Simulated IR BTs using Objects

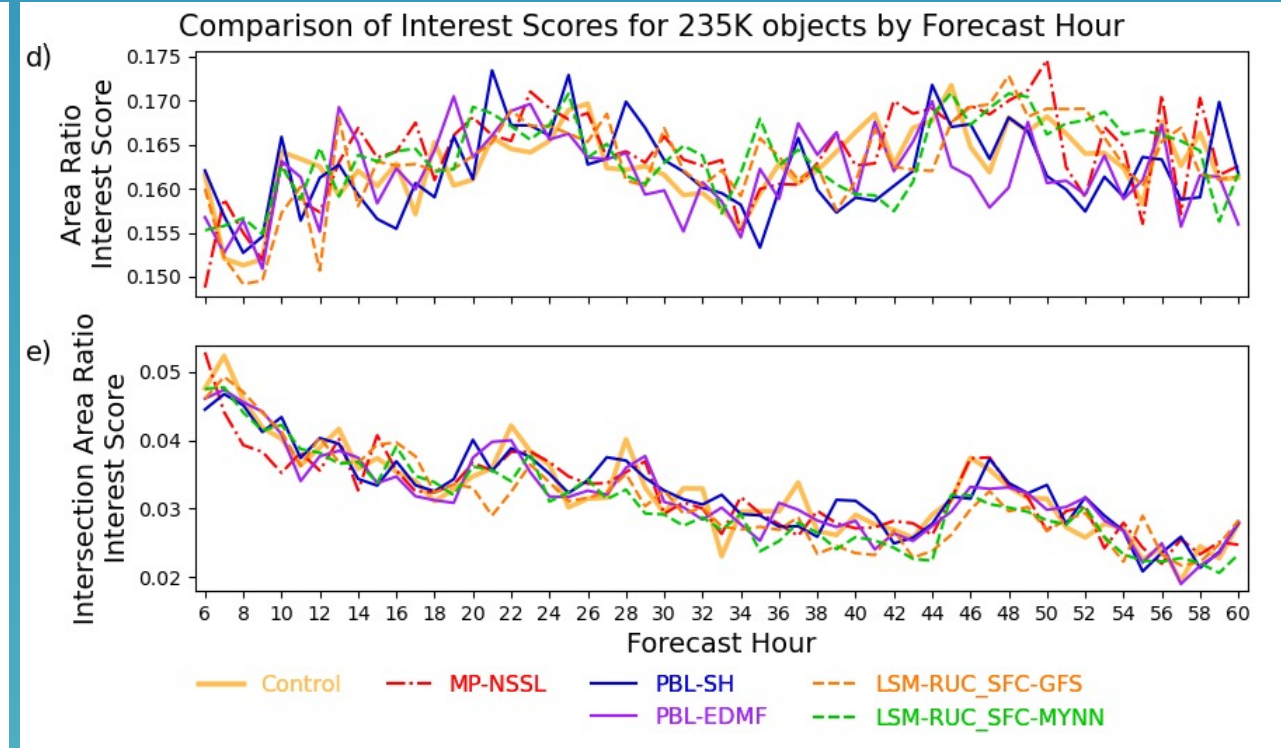
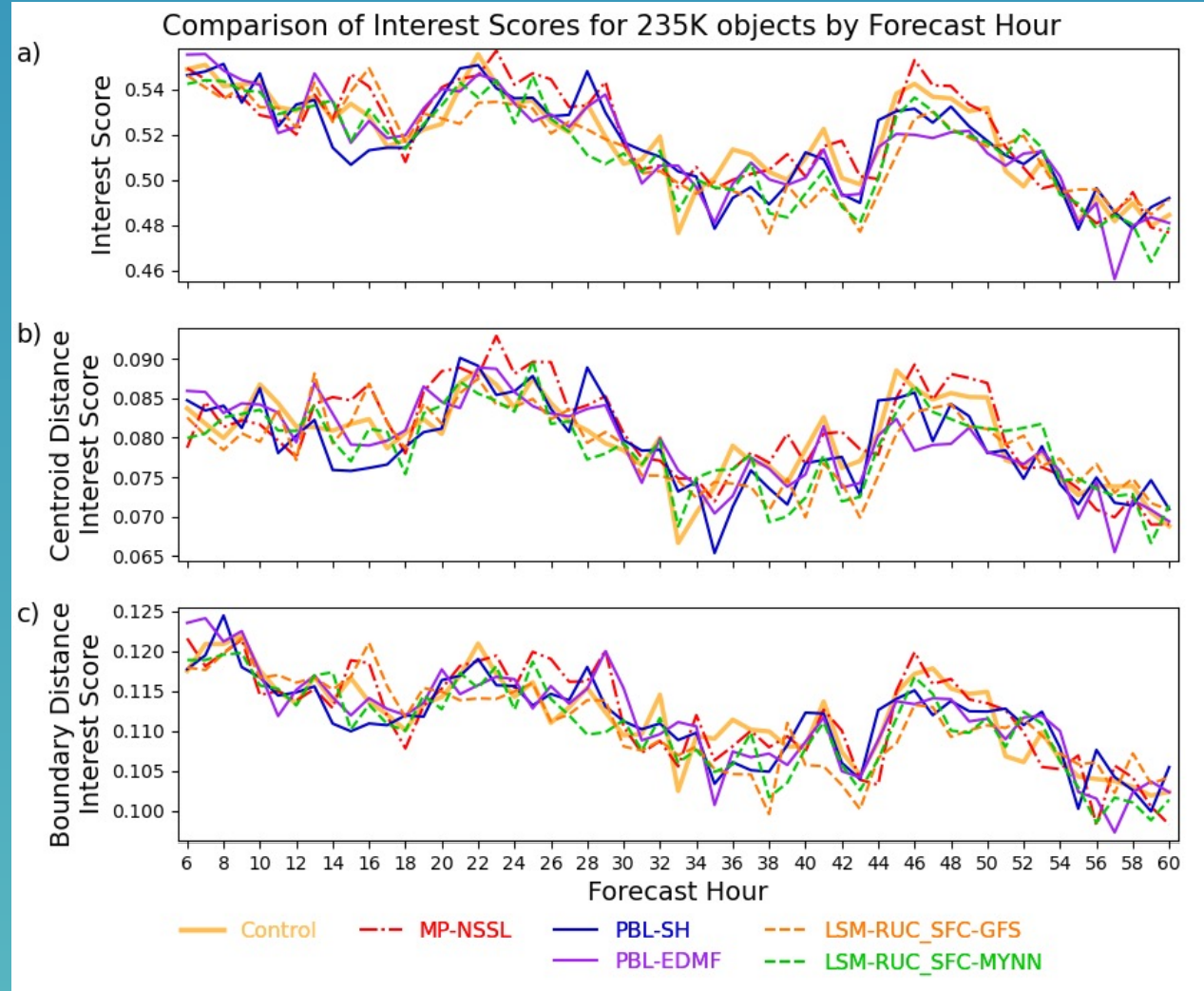


LSM-RUC\_SFC-MYNN forecasts have the lowest percent of forecast area matched later in the forecast cycle.

Local maxima in Average Interest Scores.

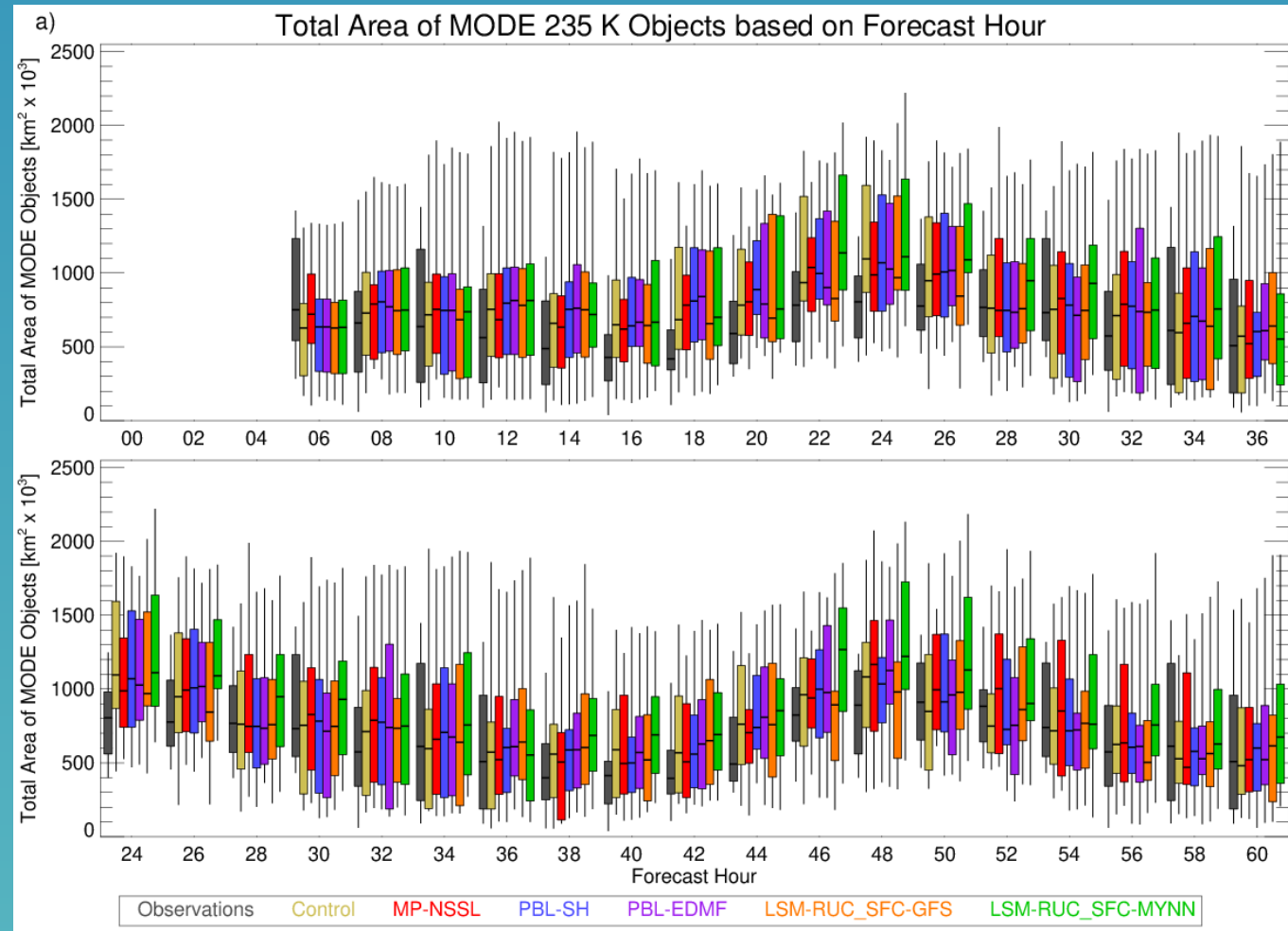
What are causing them?

# Identifying Errors in Simulated IR BTs using Objects



Same cyclic nature in the distance attribute interest scores as the overall interest score.

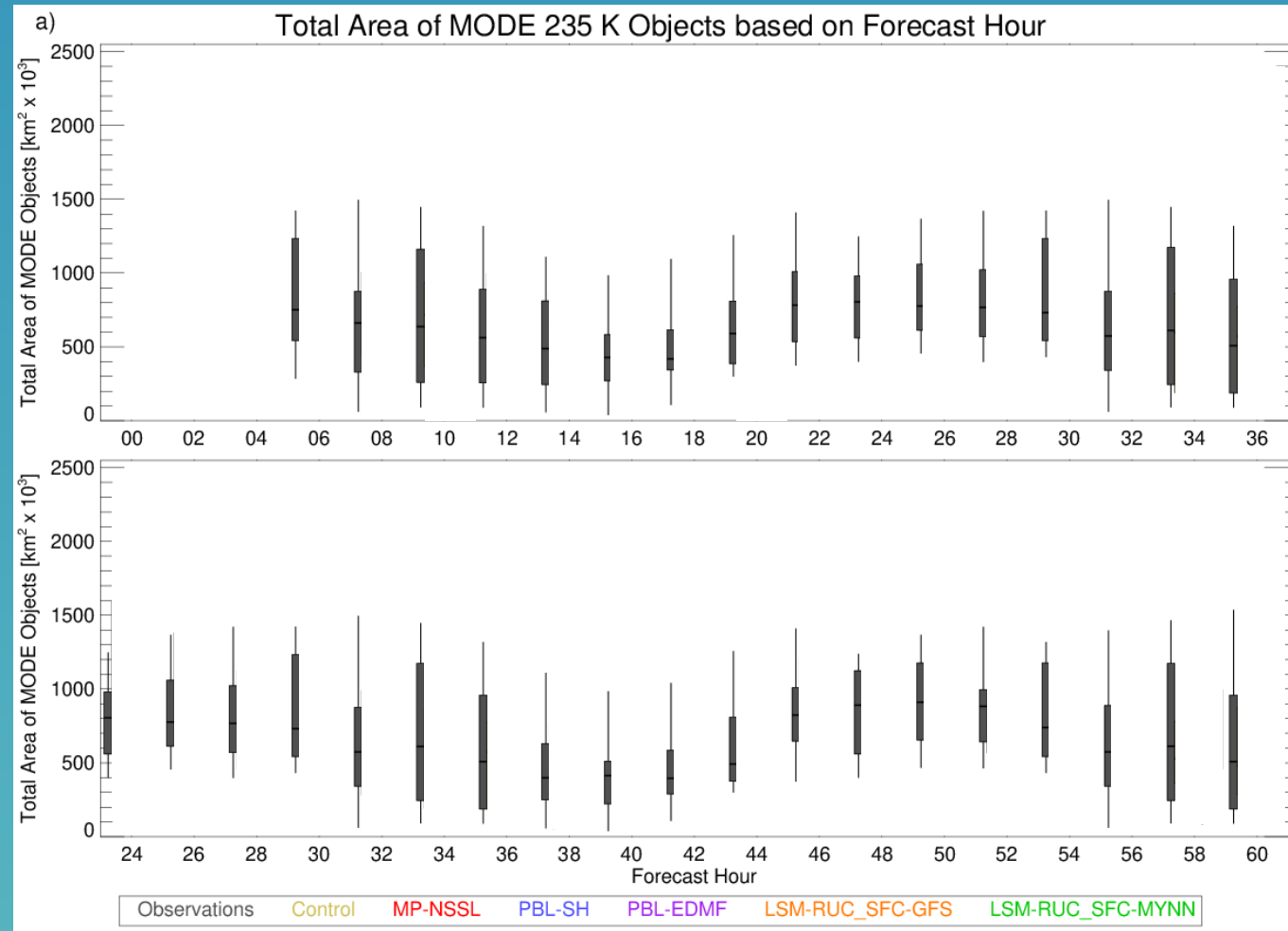
# Identifying Errors in Simulated IR BTs using Objects



Cyclic nature in the total area of MODE objects, highest at forecast hours 24 and 48.



# Identifying Errors in Simulated IR BTs using Objects



Cyclic nature in the total area of MODE objects, highest at forecast hours 24 and 48.

Not as apparent in just the observations, which is possibly why this cyclic nature is not in area ratio.

# Conclusions

- 1) Simulated BTs are a proxy for clouds.
- 2) Traditional metrics, like MAE, can verify cloud forecasts but they do not account for displacement.
  - a) We can calculate Mean Difference based on a BT threshold for a cloud.
- 3) Use MODE to define objects in BT imagery.
  - a) Remove displacement between object pairs.
    - i. Thompson microphysics scheme produces the most accurate object BTs.
    - ii. MYNN surface layer has a less negative MBE between paired objects than GFS.
  - b) Calculate OTS and its components to assess accuracy.
    - i. Rapid decrease in accuracy with the RUC LSM compared to Noah.
    - ii. Too many forecast objects resulted in lower percentage of paired forecast objects.
  - c) Local maxima in interest scores at 00 UTC.
    - i. Due to paired objects being closer together.
    - ii. Area of forecast objects are cyclic, but observation area is not.