

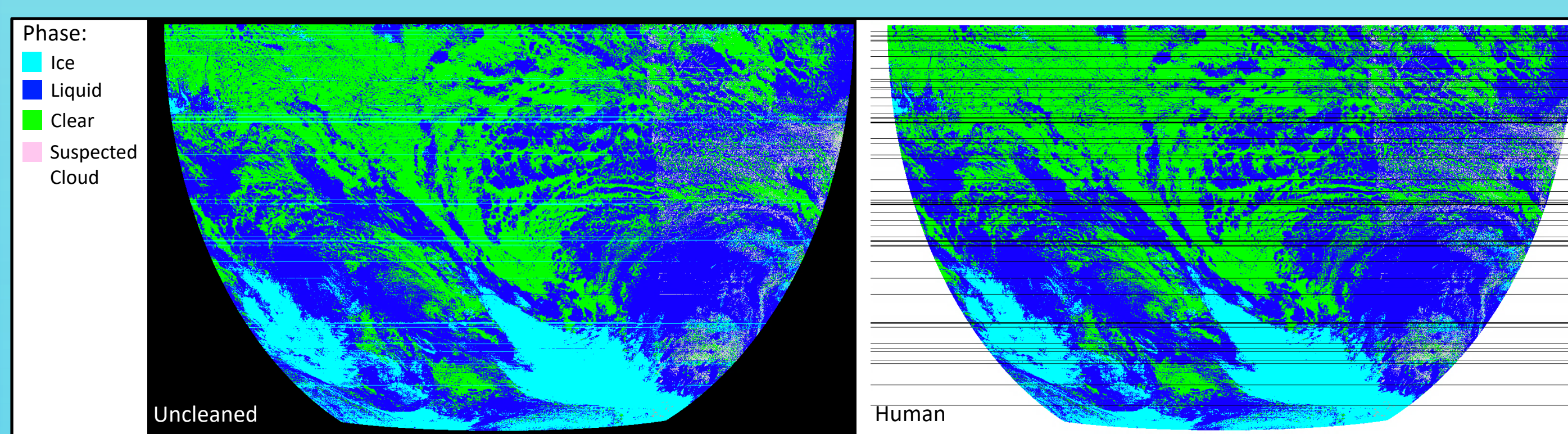
Introduction

Various AI/ML tools, employed within the Clouds and the Earth's Radiant Energy System (CERES) Satellite Cloud and Radiation Property retrieval System (SatCORPS) project, are being used to mitigate satellite radiance artifacts and thereby yield more accurate cloud and radiation data products. Neural network and K-nearest neighbor approaches have been developed that enable us to better address common passive satellite remote sensing challenges, such as corrupted imagery, day/night cloud property discontinuities, solar terminator artifacts, inadequate knowledge of the land surface emission temperature (i.e., skin temperature), and poor assumptions about vertical cloud structure, that have otherwise proven difficult to solve using more conventional methods. Fixing these problems promotes a more consistent Earth radiation budget record. These efforts demonstrate effective use of AI/ML architecture to exploit complex, multivariate predictor relationships and produce usable output at satellite spatial and temporal resolutions that would otherwise be ignored or have large biases.

Image Quality: Mitigating Bad Scan Lines

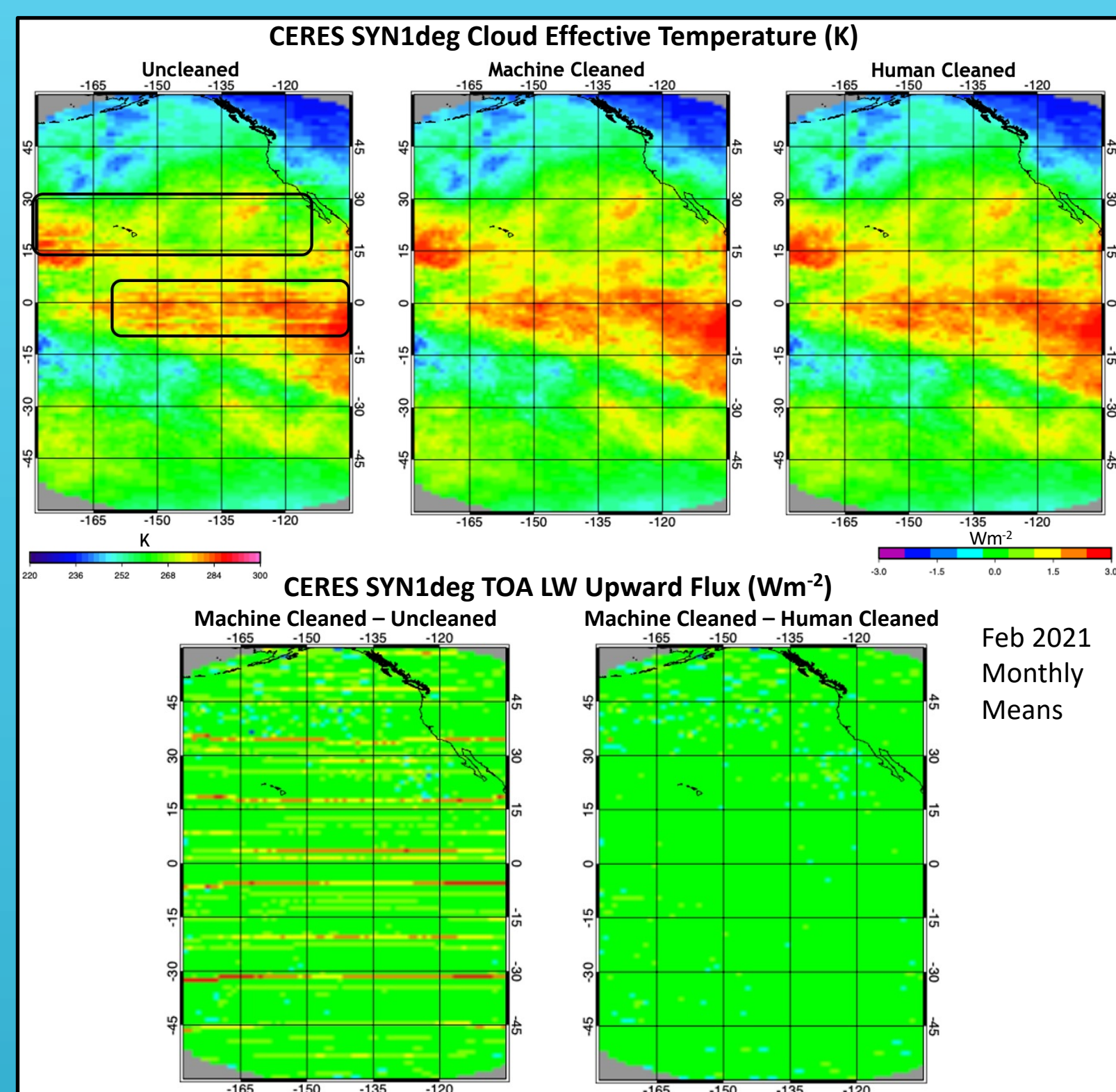
Background:

- The Clouds and the Earth's Radiant Energy System (CERES) project provides a satellite-based global climate data record (CDR) of Earth's radiation budget and clouds
- GOES-17 ABI has a cooling system anomaly that results in many bad scan lines at night



Problem:

- Unmitigated bad scanlines may contain radiance values within valid range that can negatively impact derived data products
- Manually searching and flagging these is laborious and expensive but undertaken for a long time to minimize impacts to CERES CDR



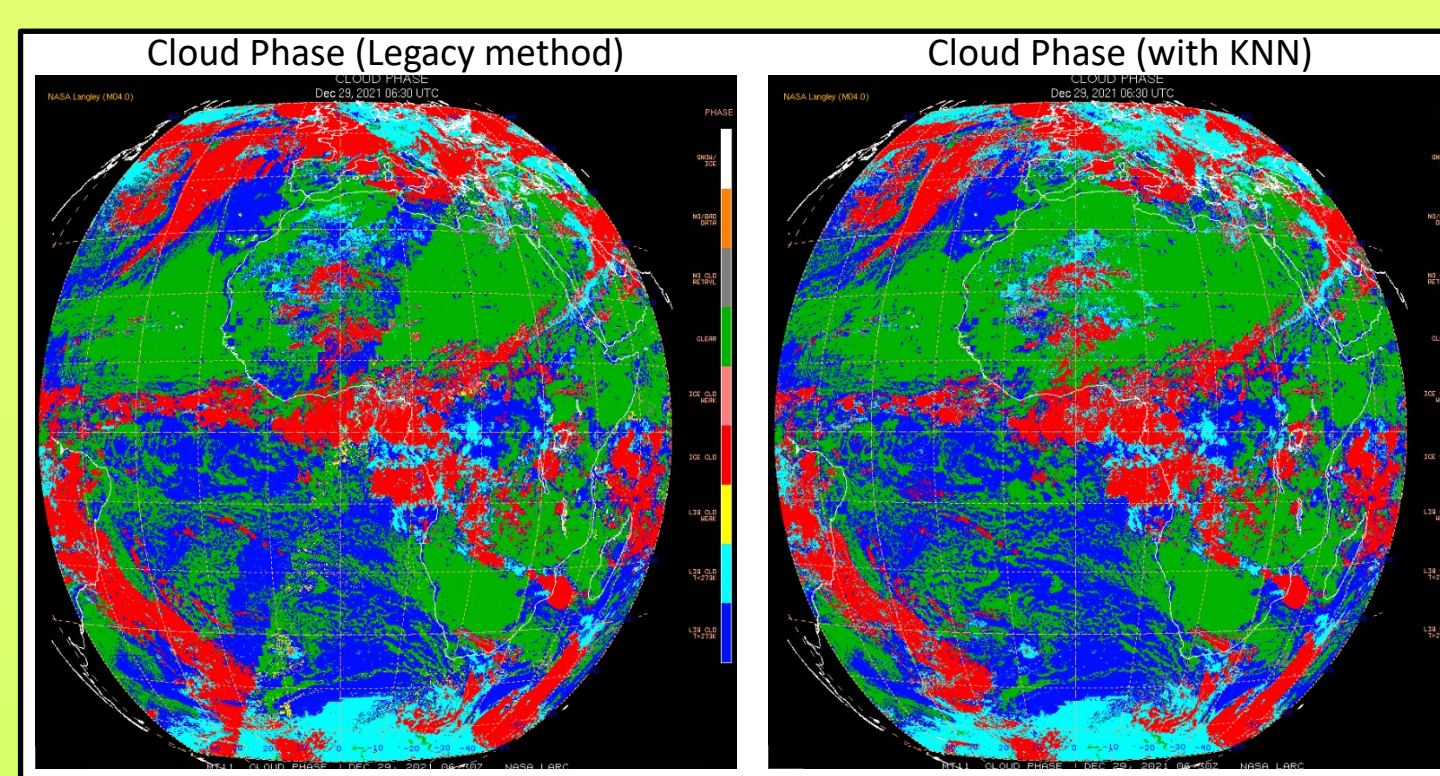
Solution:

- Train a Convolution Neural Network (CNN) to identify and "clean" bad scanlines
- CNN cleaning is simple, fast, and comprehensive

Outcomes:

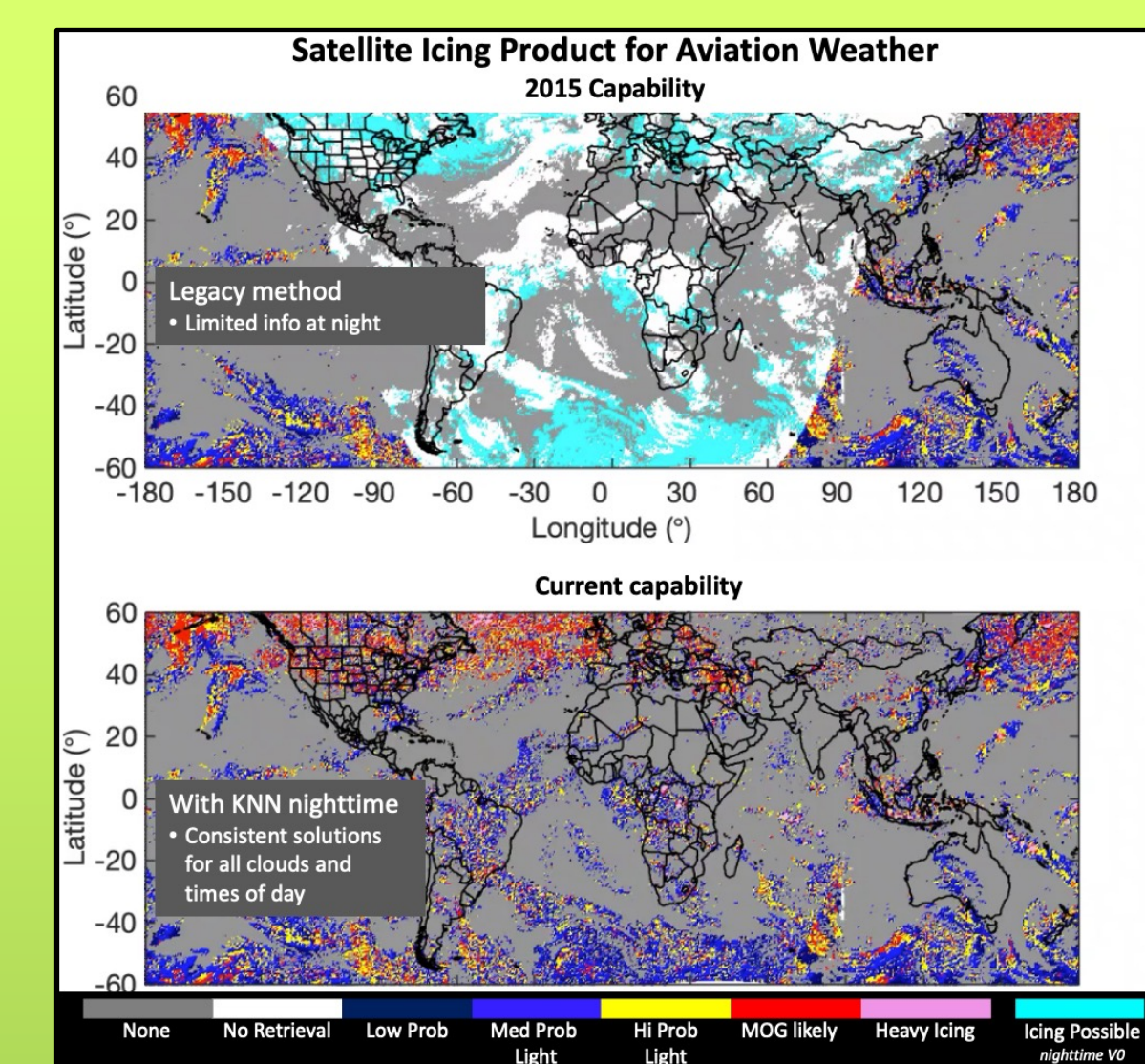
- CNN approach effectively eliminates artifacts in derived products (CERES-SYN1deg shown here)
- Much more efficient and at least as accurate as manual approach
- Enables effective use of GOES-17 nighttime data in operation systems within CERES

KNN Solutions for Terminator and for Aircraft Icing



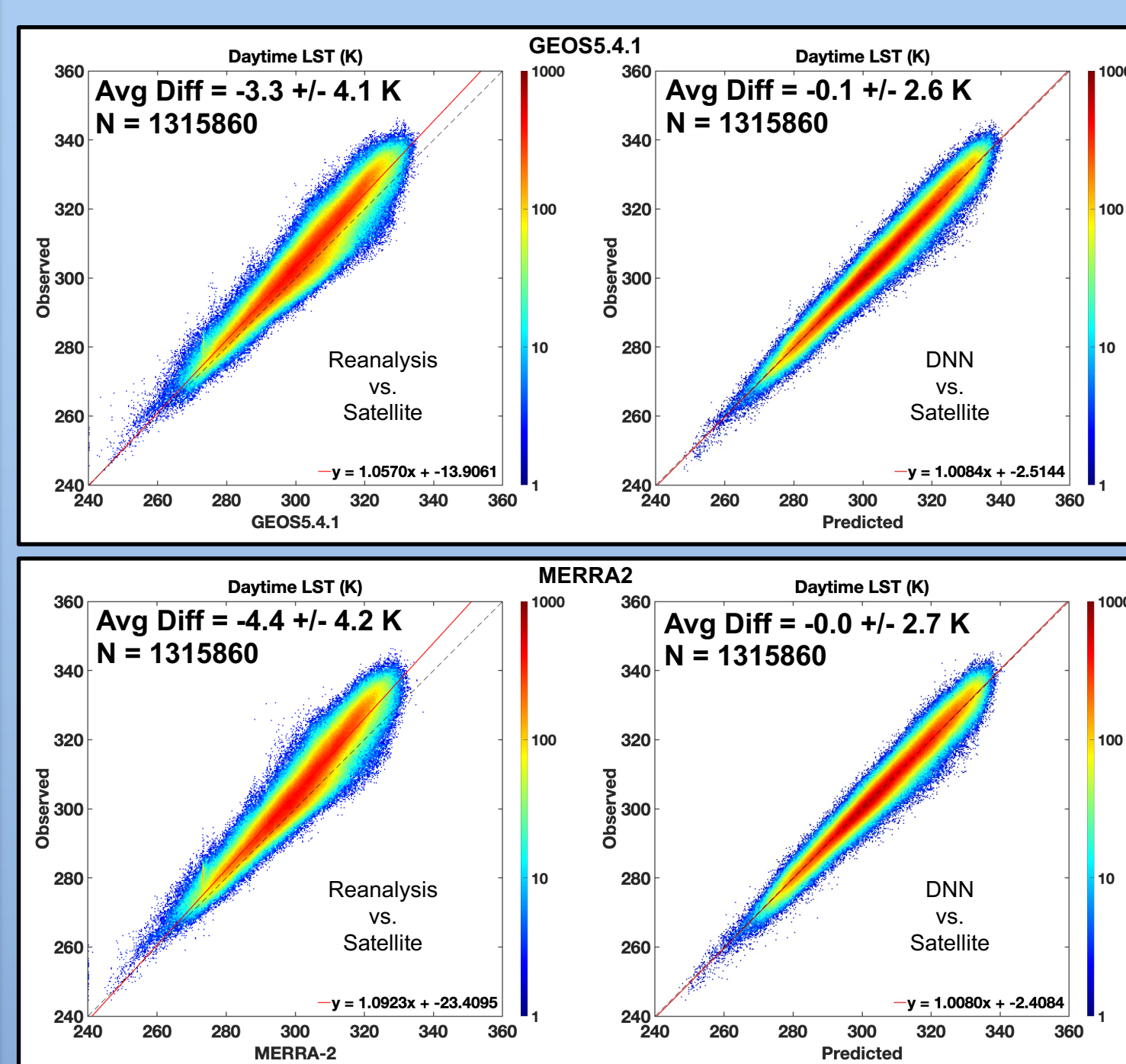
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- Incorrect phase classification in solar terminator can affect downstream parameters
- KNN method significantly reduces artifacts in the terminator



- Aircraft icing threat is associated with optically thick clouds containing SLW
- Satellite method fuses information from imagers (COD, Z, Re) with information CloudSat, cloud models, MWR, and aircraft data to estimate probability and severity of icing
- Global satellite icing grids are used to validate icing weather tools at the AWC and WAFc
- New nighttime optical depths derived with KNN provide consistent analyses at all times of day unlike the legacy product

Deep Neural Network for Land Surface Temperature



Background:

- Threshold approaches for cloud detection rely on an estimate of the surface emission land surface temperature (LST) which is often obtained from NWP/reanalysis data

Problem:

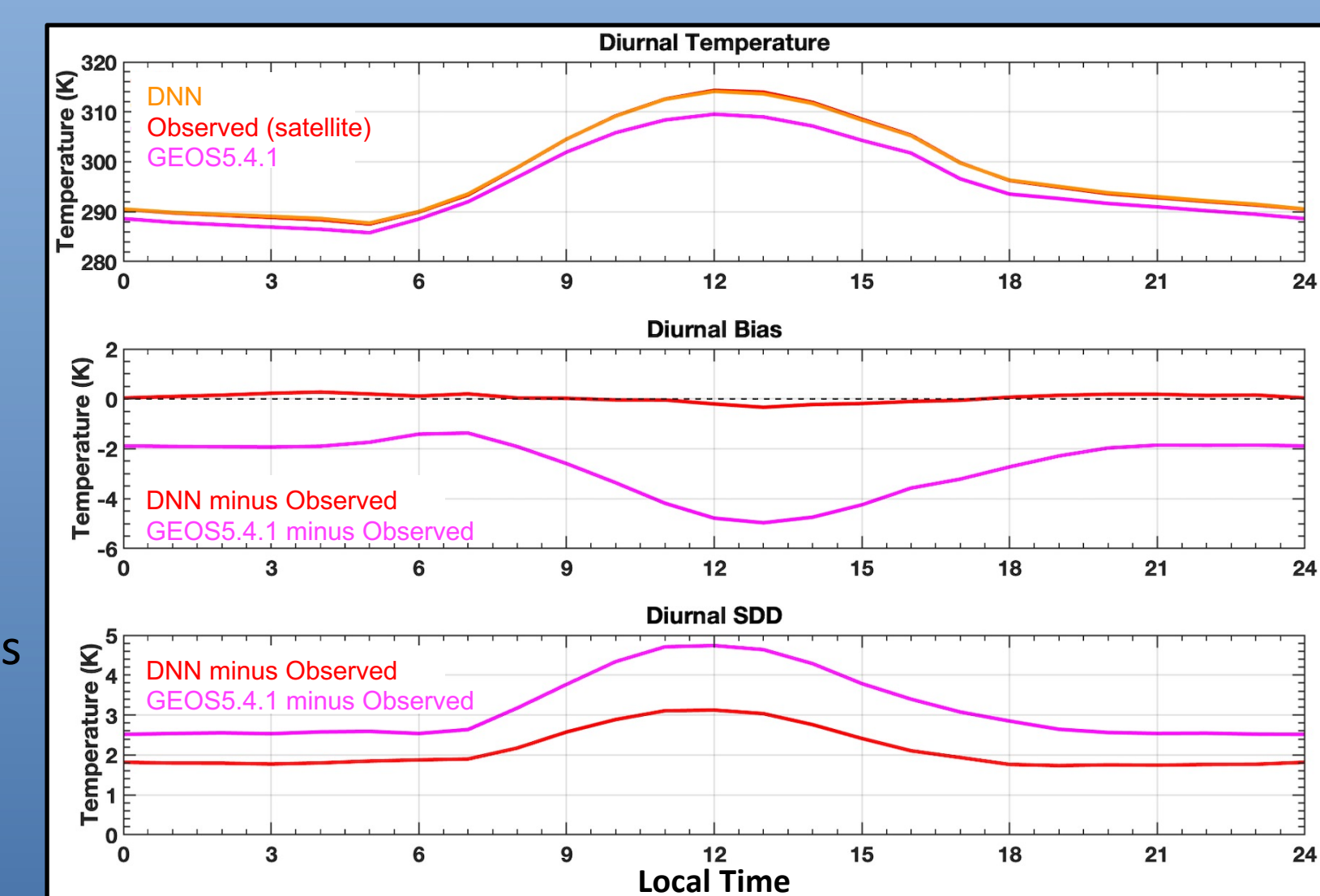
- Models and observations found to disagree in clear conditions (diurnal dependence)
- Differences vary among models but significant for all

Solution:

- Train Deep Neural Networks to tie reanalysis air temperature to satellite-observed LST in cloud free conditions

Outcome:

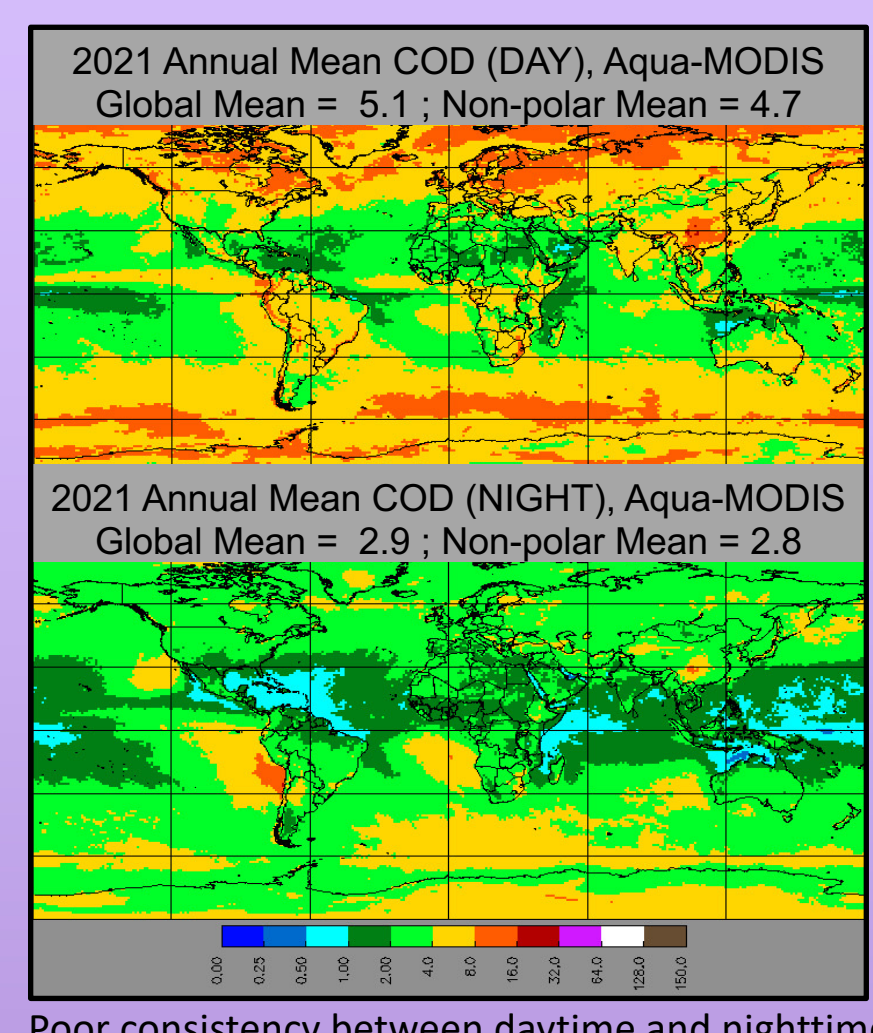
- DNN approach effectively removes diurnally dependent regional differences found between reanalysis LST's and observations
- Should lead to improved regional accuracies in cloud detection



Nighttime Cloud Optical Depth (COD)

Problem:

- COD can be estimated theoretically from solar channels over a wide range during daytime
- At night, only thin cloud retrievals are theoretically possible (COD < ~6) due to IR blackbody limit
- Optically thick COD's are set to pre-assigned fill values (not consistent with daytime retrievals)
- Other parameters derived from COD at night are also inconsistent and less accurate than those for daytime (e.g., CWP, SFC LW↓, icing threat)



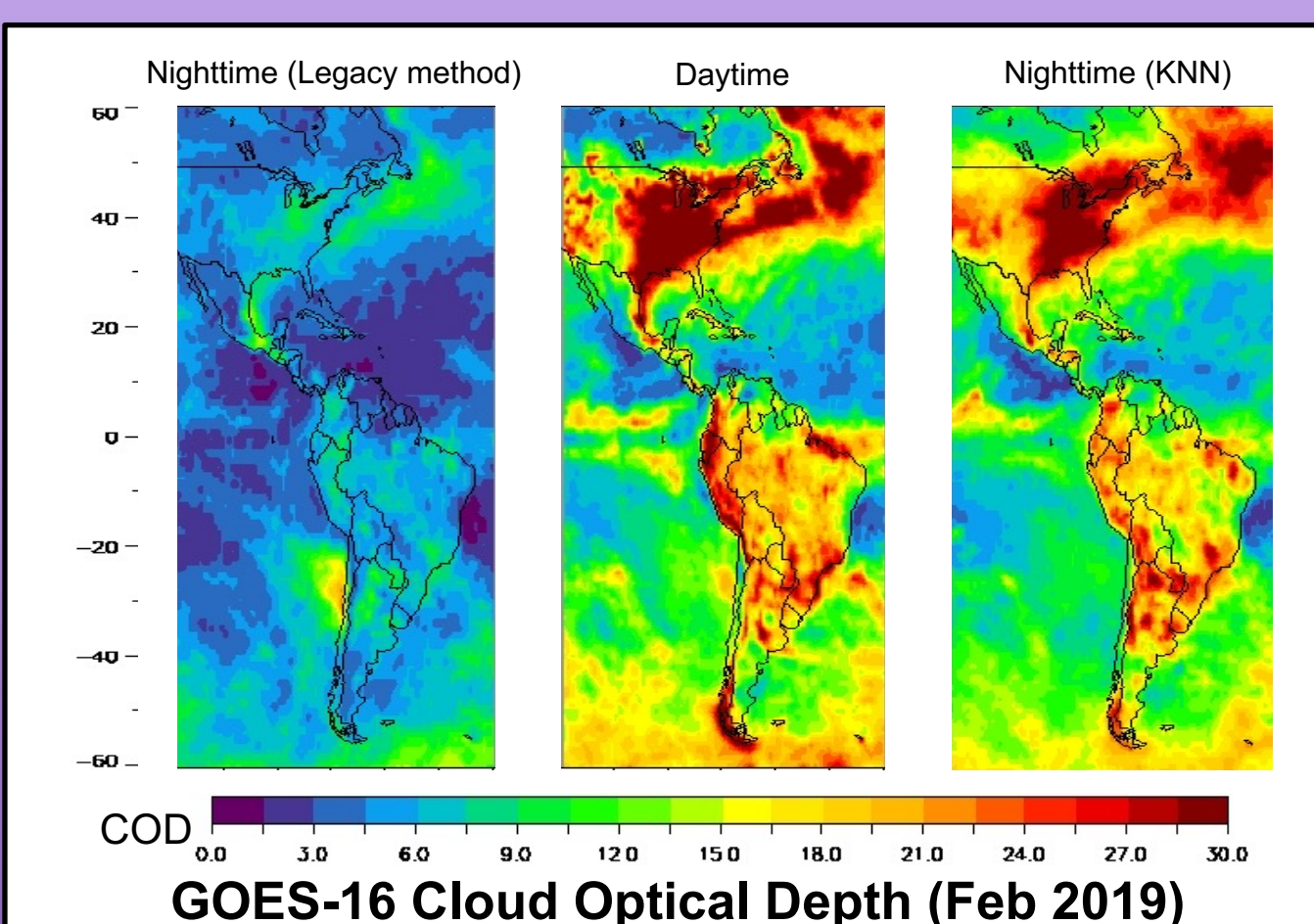
Poor consistency between daytime and nighttime

Solution:

- Apply K-nearest neighbors (KNN) method to extrapolate daytime COD into nighttime using 6.7- and 11-μm bands and local relationships with daytime COD

Outcome:

- Much more realistic filling method for nighttime optically thick COD
- More accurate downstream derived parameters



Detecting and Retrieving Multilayer (ML) Cloud Properties

Background:

- CERES developed and applied a theoretical ML retrieval algorithm to Aqua & Terra MODIS data

Problem:

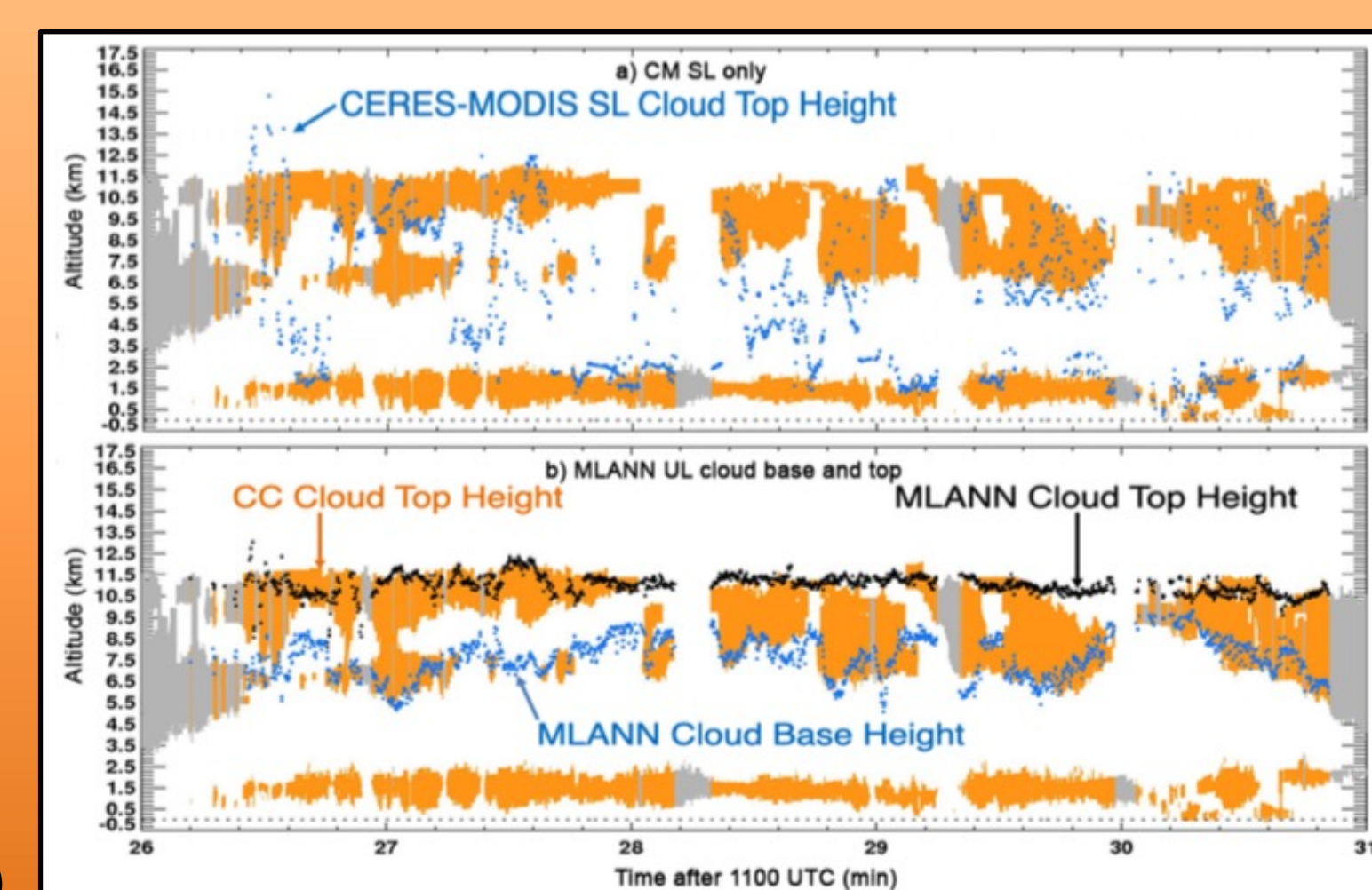
- While height and optical depth retrievals for 2-layer systems were found to be reasonably accurate, the method had very poor skill in discerning ML from SL clouds (no practical value)

Solution:

- Train an ANN to discern ML systems from SL systems using CloudSat CALIPSO data as ground-truth

Outcome:

- ANN better detects overlapping thin cirrus than previous method
- ML detection accuracy 75-80% (big improvement)
- Top/base heights for upper layer more accurate
- Is this accurate enough for applications? TBD



Conclusions

- Within SatCORPS, various AI/ML tools are being used to correct level 0 satellite radiance artifacts and to derive more accurate level 2 cloud and radiation data products
- Neural networks and KNN enable us to better address common passive satellite remote sensing challenges that have proven difficult using more conventional methods
- Some of these are ready for implementation (e.g., nighttime COD, skin temperature), others need more work and testing (e.g., multilayered clouds, cloud thickness)
- Cloud computing infrastructure is enabling improved processing capabilities (higher resolutions, more satellites) – leading to more useful and lower latency data products for the community