Optical Flow Applications for Meteorological Satellite Imagery and Cloud Nowcasting Techniques

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DoD Cloud Post-Processing and Verification Workshop

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Introduction/Motivation

- CIRA's OVERCAST research (sponsored by U.S. Navy Office of Naval Research)
    - Aims to develop an advanced global 3D cloud structure analysis based on current satellite remote sensing capabilities
- 3D Cloud Nowcasting is a key milestone for OVERCAST research
- For DoD operations, having accurate cloud locations is important for aircraft hazards & visibility
- Mission success for Intelligence, Surveillance, and Reconnaissance (ISR) operations is particularly vulnerable to cloud-free-line-of-sight (CFLOS) requirements to surface targets

Background on past methods

- Advection Methods
  - Air Force Advect Cloud Model – advects cloud moisture parameter (Storch and McDonald, 2001)
  - Multi-sensor Advection Diffusion nowcast (MADCast) – WRF model advection/diffusion ((Jiménez et al. 2022)
  - CIRA-Cast – cloud grouping based on properties with forward advection (Miller et al. 2018)
- Optical Flow Nowcasting
  - Radar Nowcasting of Precipitation and Winds – Radar-based optical flow nowcasting (Bechini and Chandrasekar 2017)
  - Cloud Nowcasting involving Optical Flow – 2D Piecewise optical flow field (Kellerhals et al. 2022)
- Machine Learning – Convolutional Neural Networks
  - 2d Cloud Nowcasting using Neural Networks (Berthomier et al. 2020) and (Kellerhals et al. 2022)
  - NWP Cloud Forecast Corrections – (Nguyen et al. 2023)

3D Cloud Advection Methods

- Investigated several methods of advection methods
  - All used interpolated GFS wind data
  - Filled cloud according to CLAVR-x cloud top height and cloud base height
- Found backward advection method produced best nowcast
  - Can use this as a benchmark
  - Follows method in Advected Layer Precipitable Water (ALPW) product (Gitro et al, 2018)

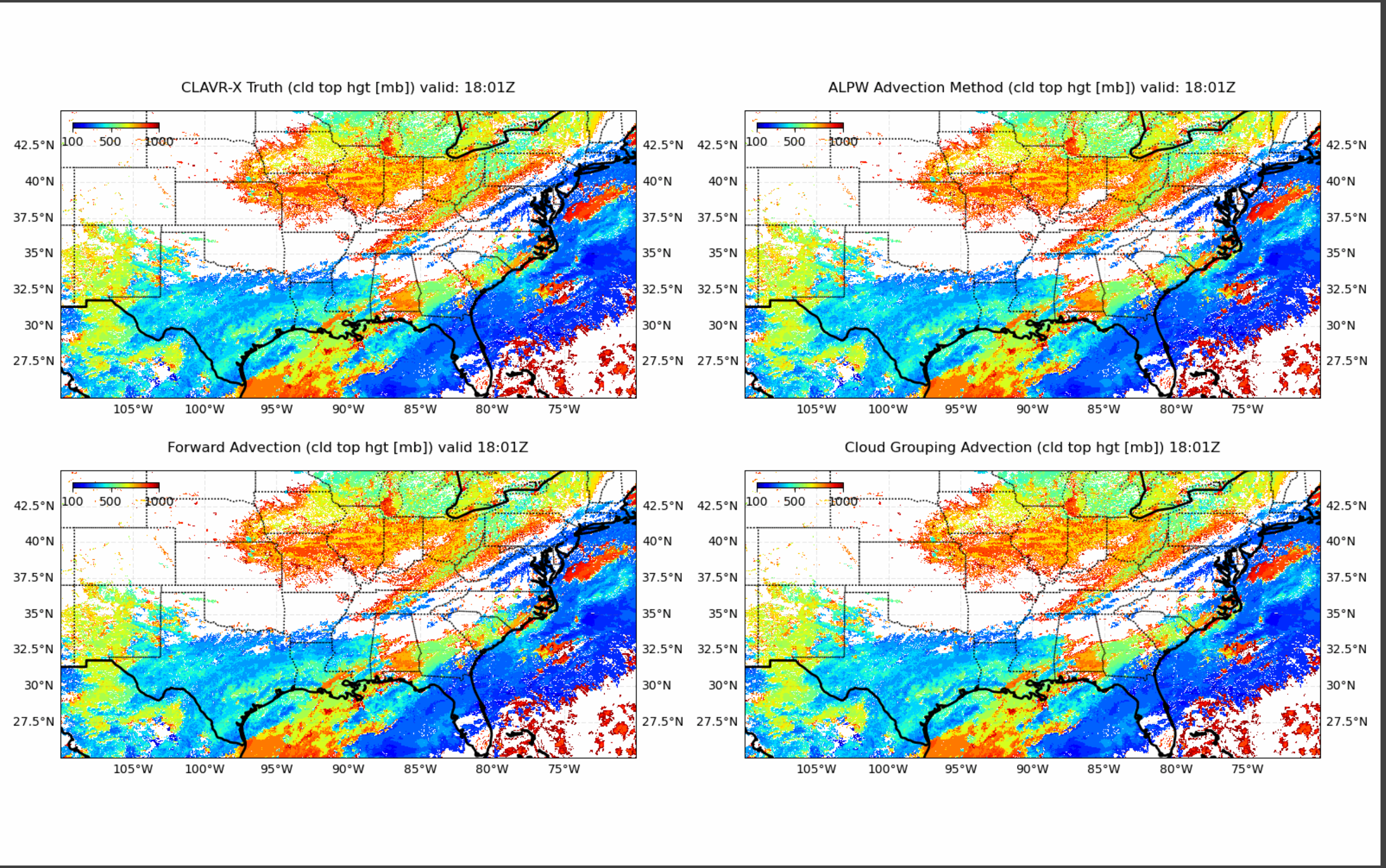

Figure 1. 3D advection cloud nowcasting example using Clouds from AVHRR Extended (CLAVR-x) as initial cloud state. Nowcast is 3 hrs in total with 15 min steps.

Validation of Advection Methods

- ALPW method does marginally better than persistence
- Issues with Advection
  - Incorrect trajectories
  - Computationally expensive
  - Doesn't form/dissipate clouds
- Address first two issues with optical flow
- Possibly address formation/dissipation with ML

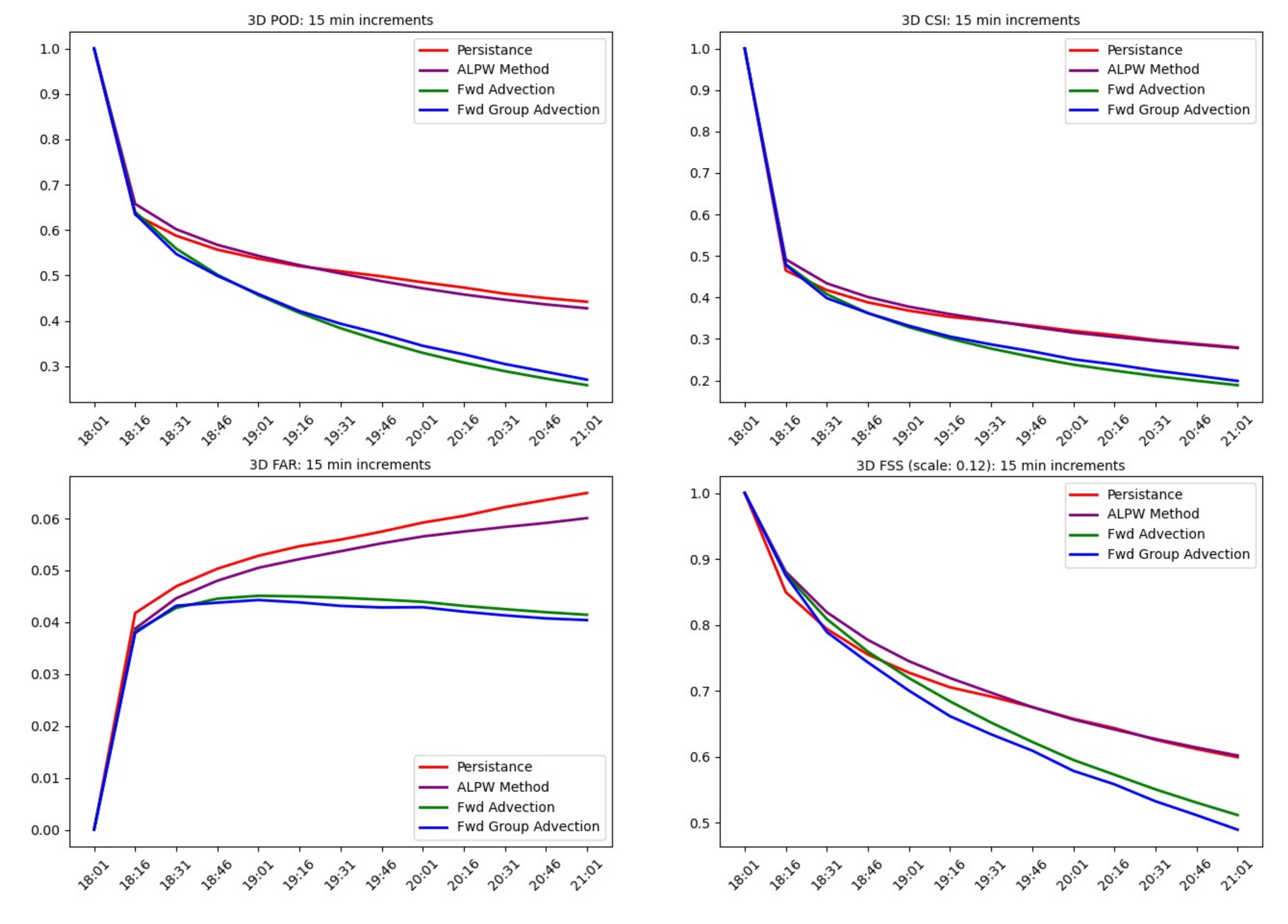

Figure 2. Probability of Detection (POD), Critical Skill Index (CSI), False Alarm Rate (FAR), and Fraction Skill Score (FSS) plots for previous nowcast example for all pressure levels.

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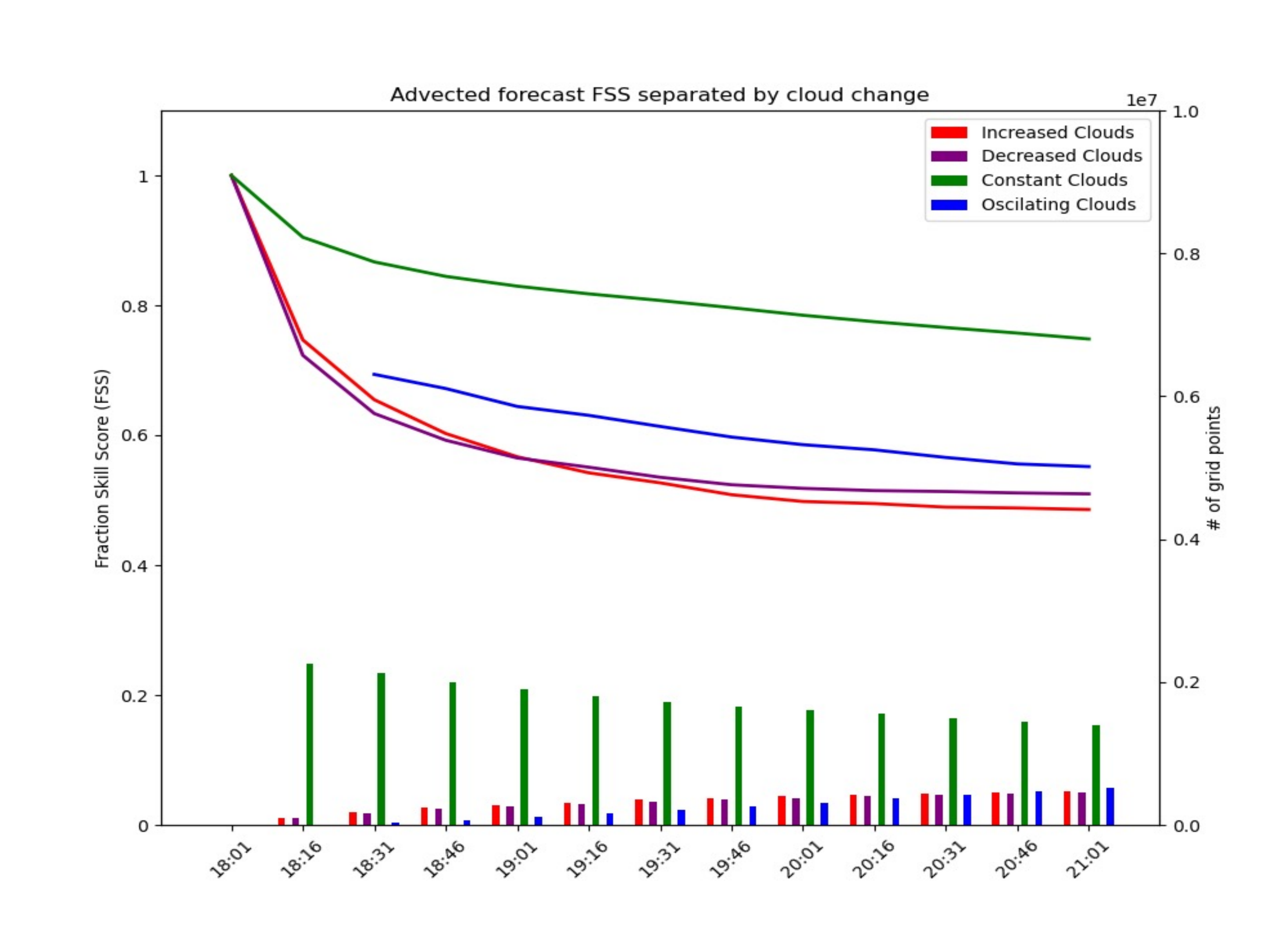


Figure 3. Fraction skill score evaluated following GFS trajectories to analyze skill for change in cloud fraction over time of nowcast.

Optical Flow

- **Optical Flow (OF) Definition:**

  "The distribution of apparent velocities of movement of brightness patterns in an image" (Horn and Schunck 1981)
- Like a different channel on an imager, OF provides unique context of an image scene for a variety of users
  - ➢ NWP
  - ➢ Forecasters
  - ➢ Machine Learning/AI
- OF is an important tool for 3D cloud diagnosis and nowcasting with multiple satellite imagers!
- OF computed here using the Optical flow Code for Tracking, Atmospheric motion vector, and Nowcasting Experiments (OCTANE; Apke et al. 2022; https://github.com/JasonApke/OCTANE)

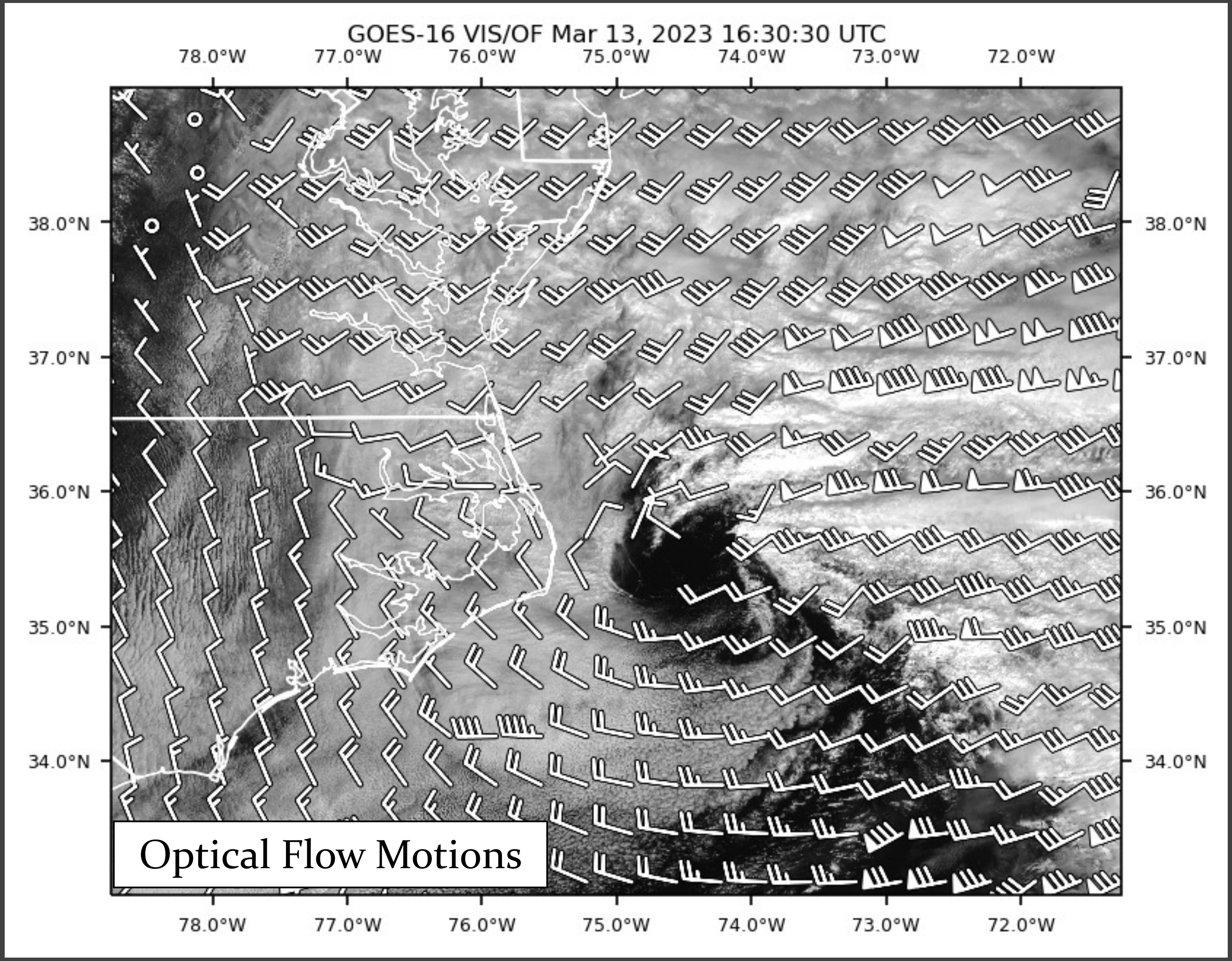
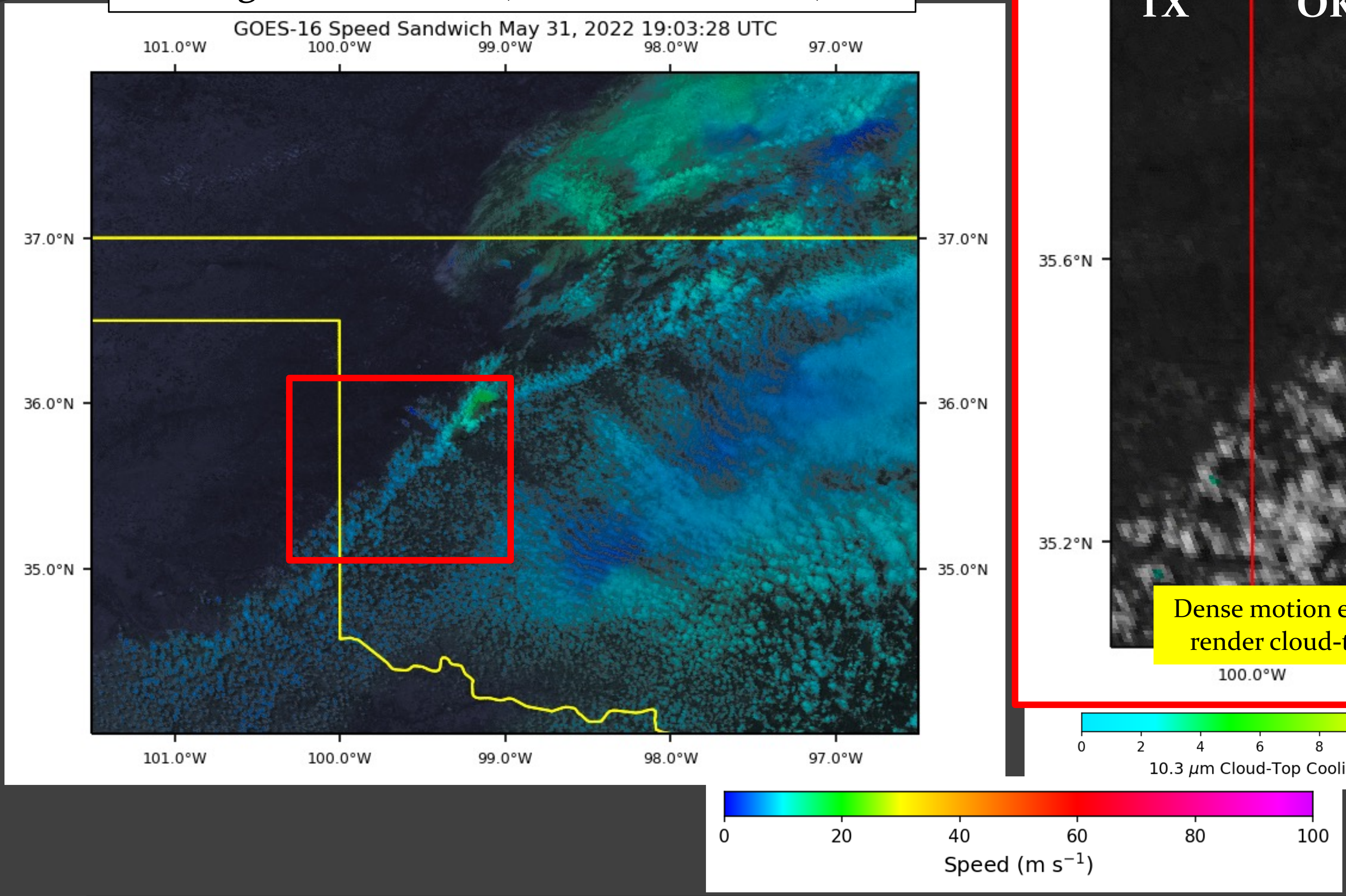


Figure 4. GOES-16 Ch-02 0.64 µm imagery plotted with optical flow winds (white barbs) over a low-pressure system of the coast of VA/NC.

OF Applications Demonstrated

High Wind Shear (Severe Hailstorms)



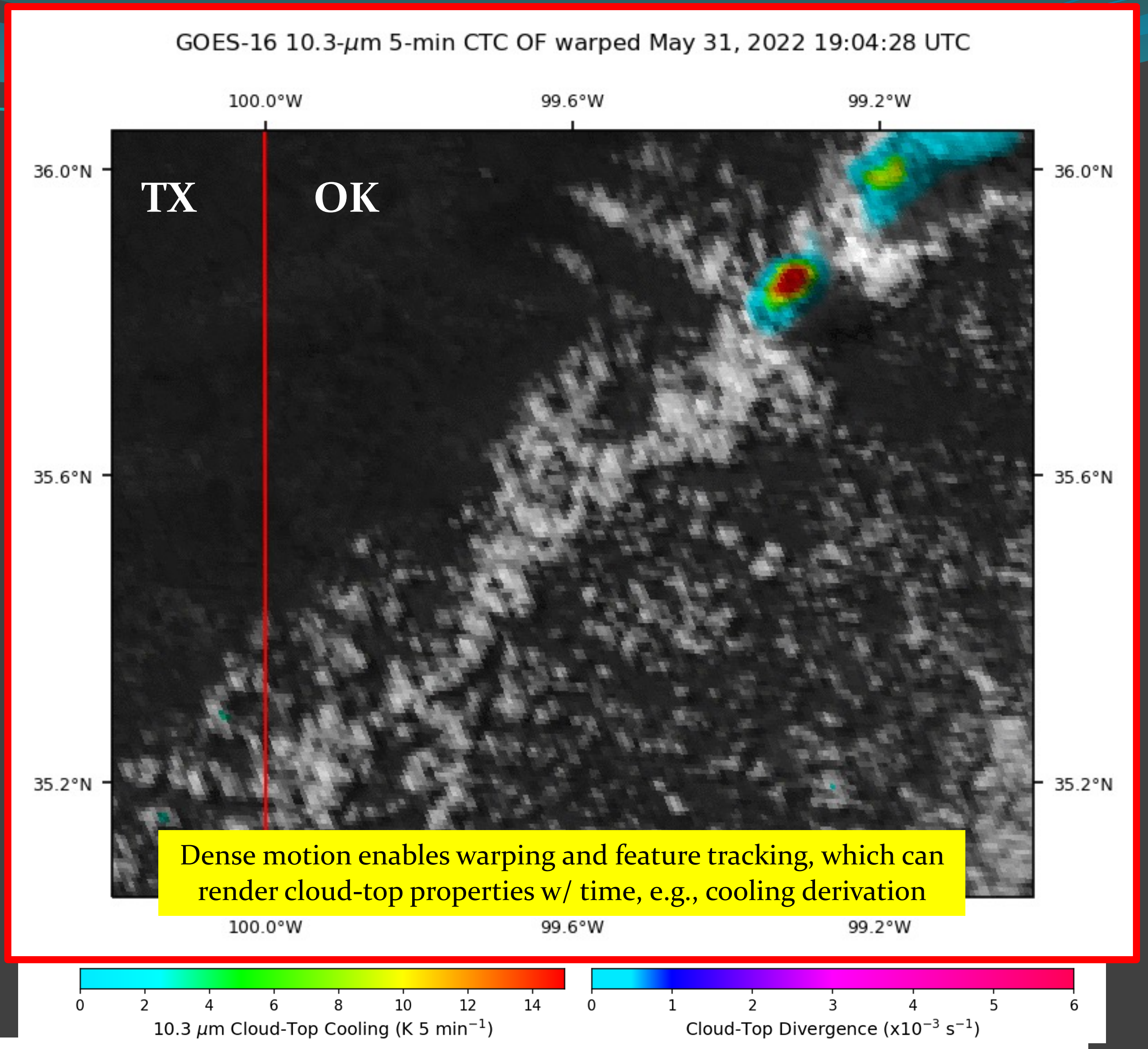


Figure 5. (*Left*) GOES-16 Day-Cloud Phase enhancement (from 0.64, 1.6, and 10.3 µm imagery) shown with (*Right*) Dense optical flow colored by wind speed with brightness indicating the 0.64 µm reflectance (The Speed Sandwich product).

OF Temporal Correction & Nowcasting

IF the OF field is continuous, then backwards advection can be used!

- OF motions can be used to infer where clouds reside at future time-frames
- A convenient assumption -> The OF motions in the grid are continuous (no discontinuities)
  - True for radar data
  - False for visible/infrared satellite imagery!
- If the optical flow field were continuous, a backwards advection scheme could be used to infer the future cloud field
- With piecewise fields, it is instead better to use optical flow warping techniques which account for time-related changes to the optical flow field!
  - Note, another option would be to use objective analysis on each layer observed in the image (computationally expensive)

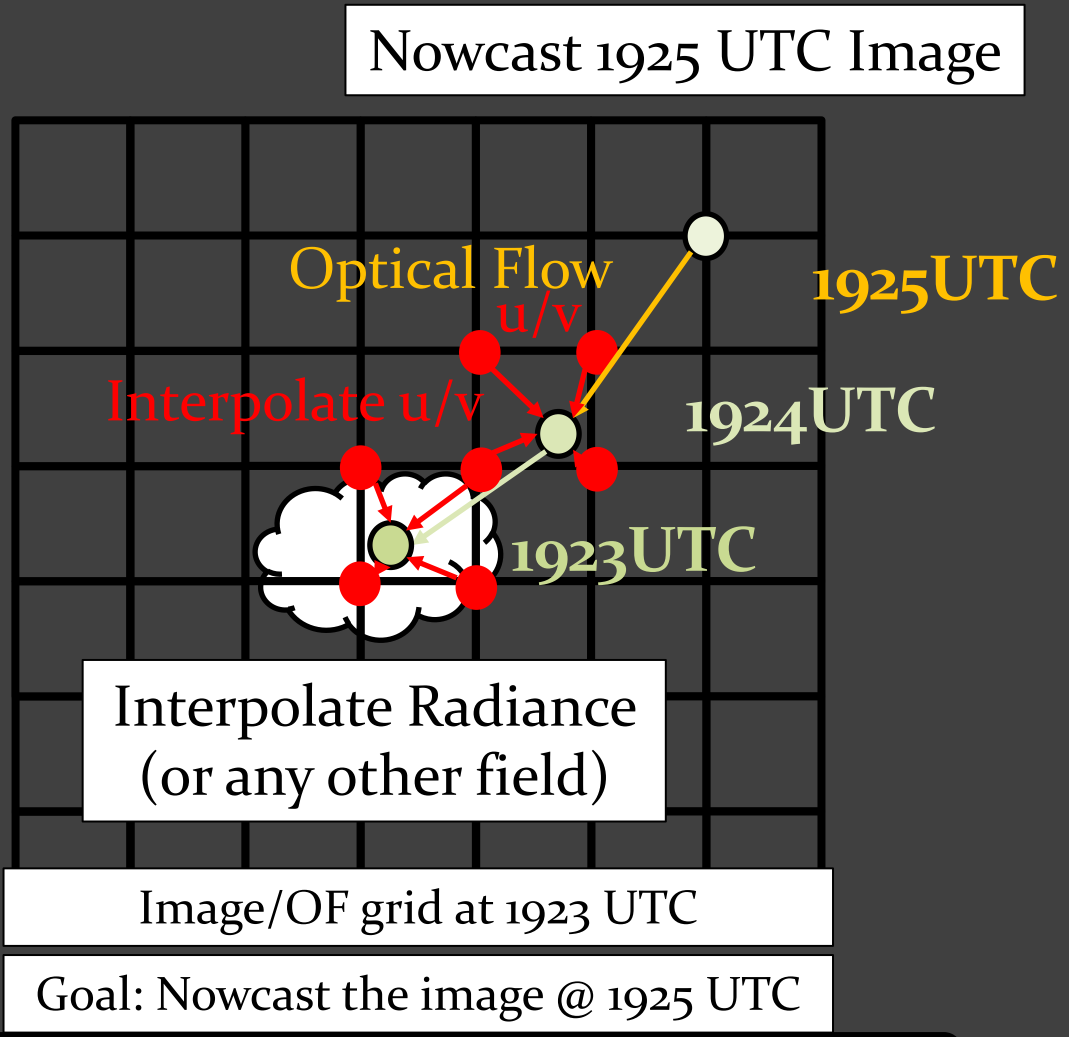


Figure 6. Schematic of continuous optical flow field-based nowcasting. With backwards advection technique.

OF Temporal Correction & Nowcasting

- One such warping technique is to first infer the optical flow field at a time of interest, then use that field to move the imagery
  - We use a method by Baker et al. 2011, includes occlusion reasoning
- This type of warping can be used to approximately increase imagery temporal resolution (MesoAnywhere)
- Can also be used to match scan times between multiple imagers
  - Useful for composites and image stereoscopy
- The forward warping process can be used to nowcast imagery using only optical flow!

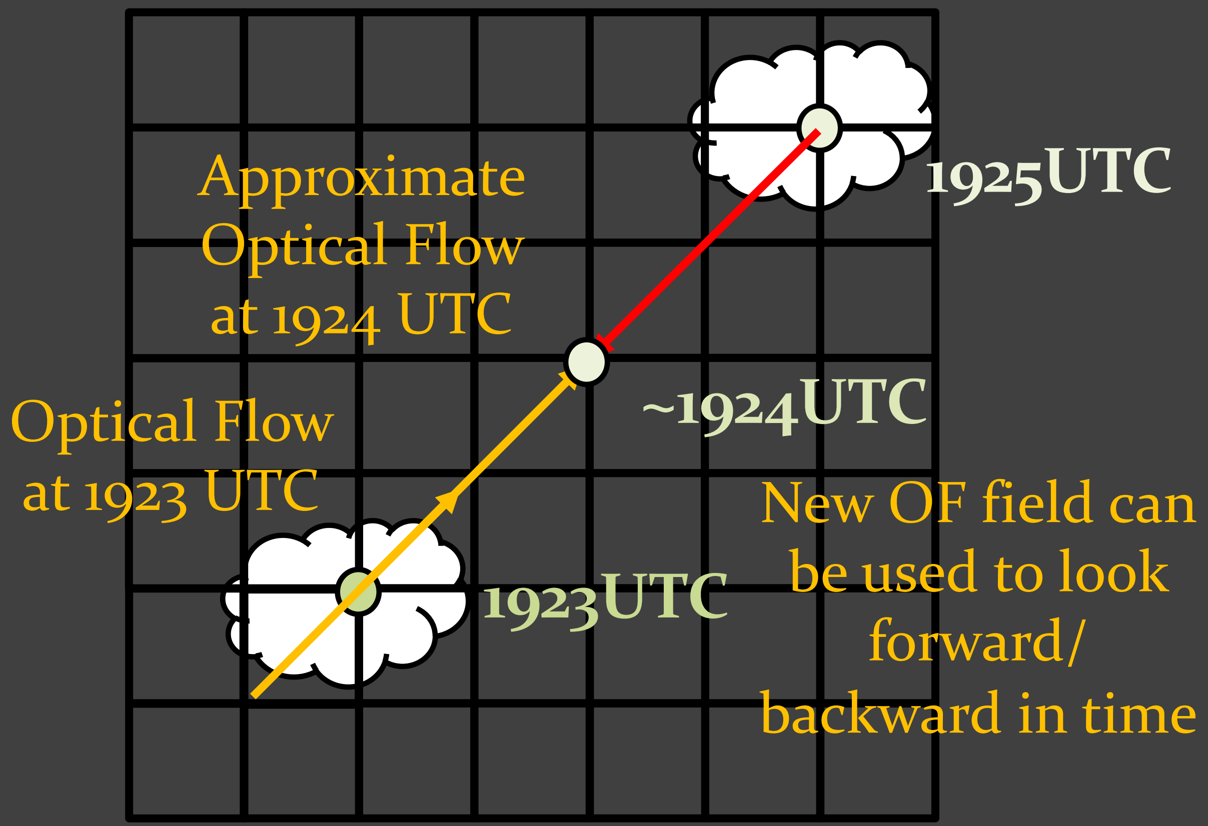
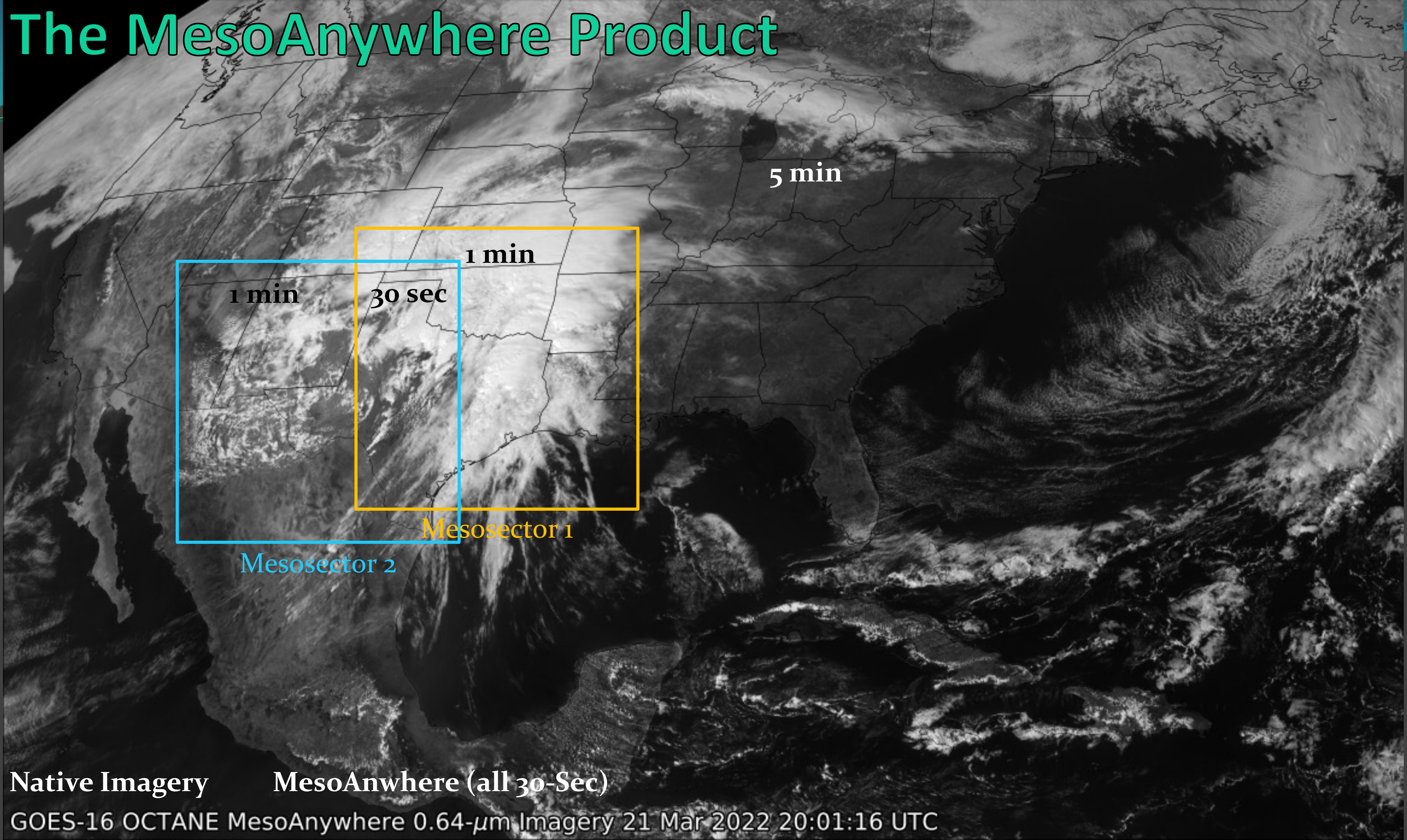


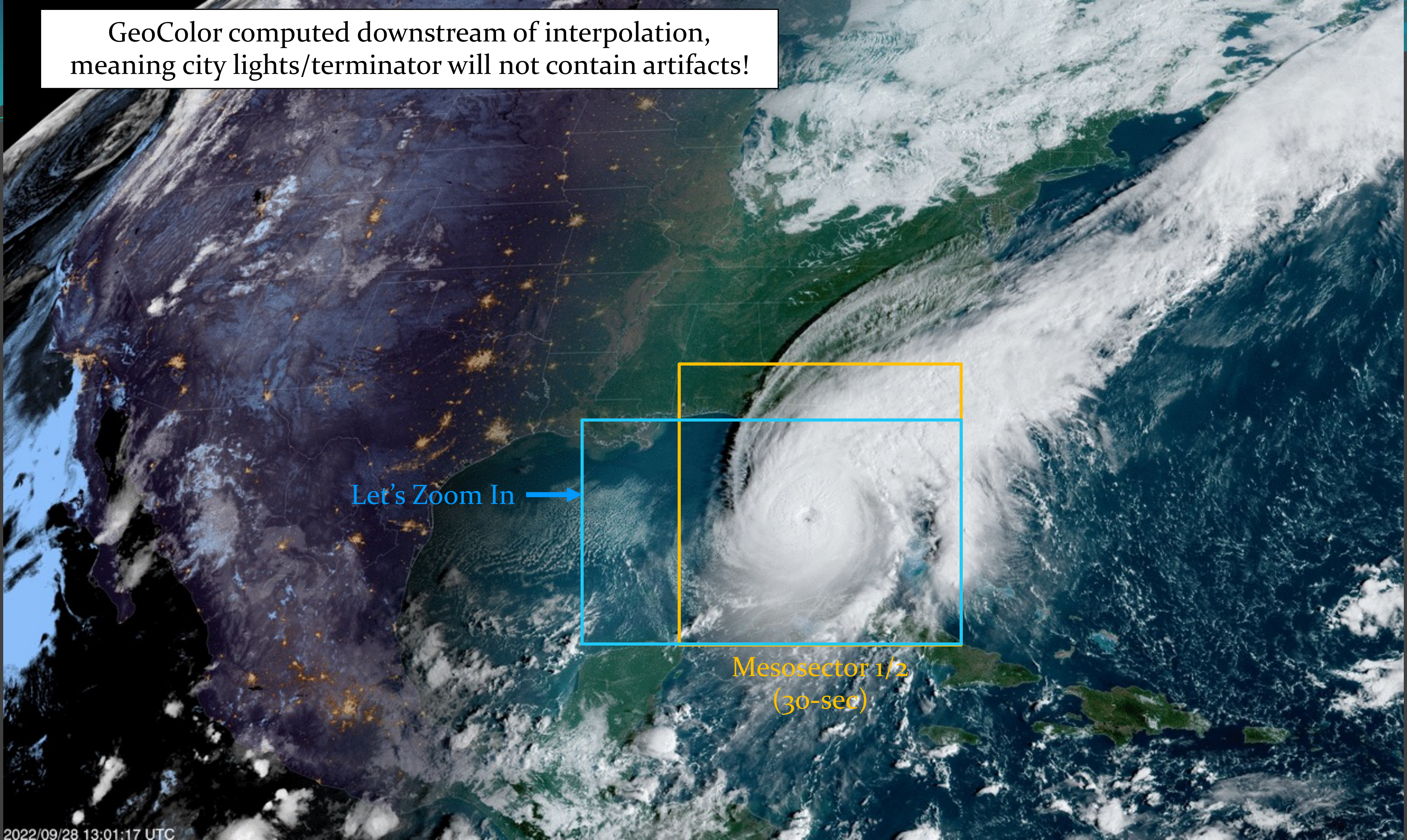
Figure 7. Schematic of optical flow temporal interpolation.

Citation: Baker, S., D. Scharstein, J. P. Lewis, S. Roth, M. J. Black, and R. Szeliski, 2011: A database and evaluation methodology for optical flow. *Int. J. Comput. Vis.*, **92**, 1–31, doi:10.1007/s11263-010-0390-2.

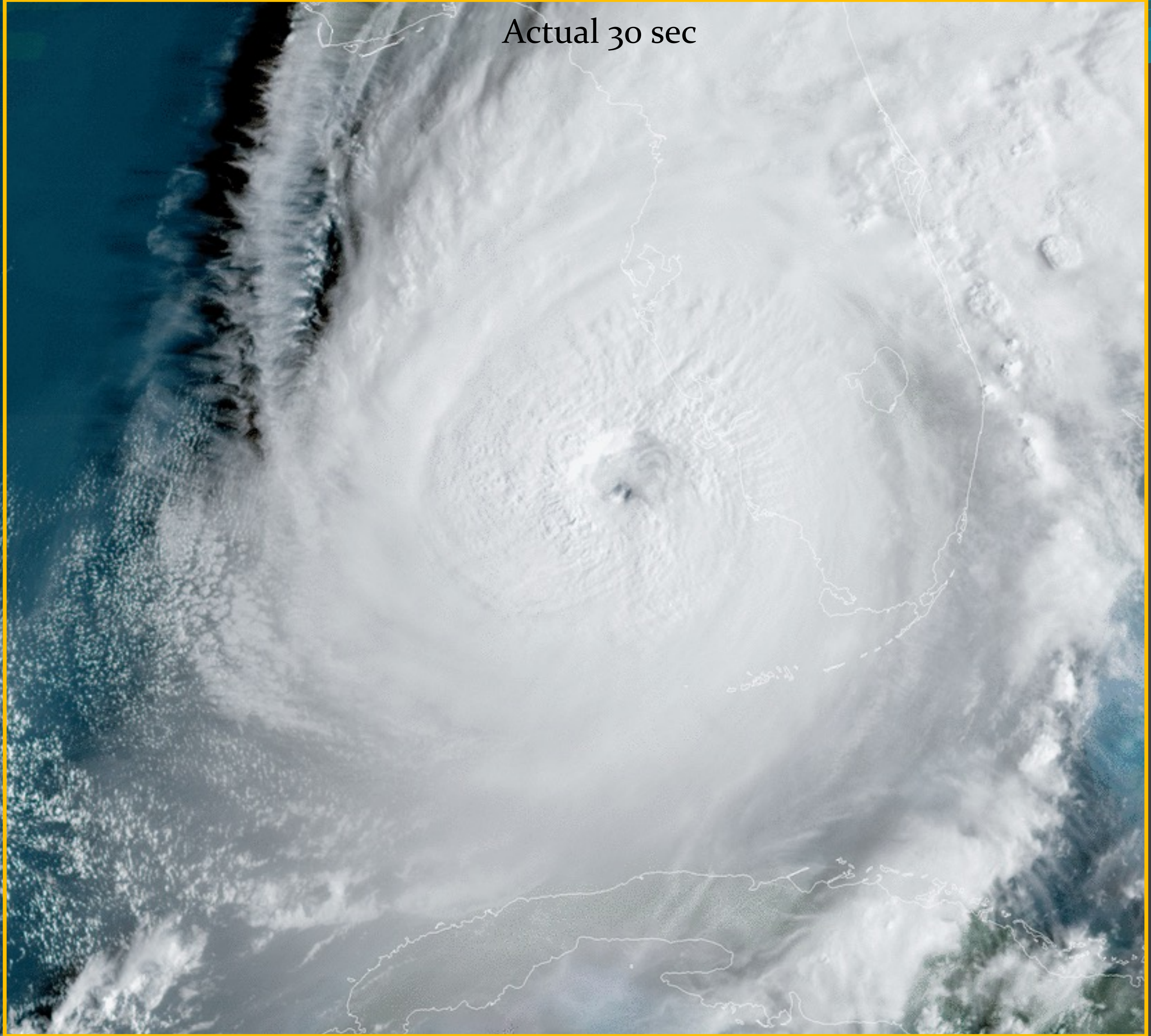
The MesoAnywhere Product



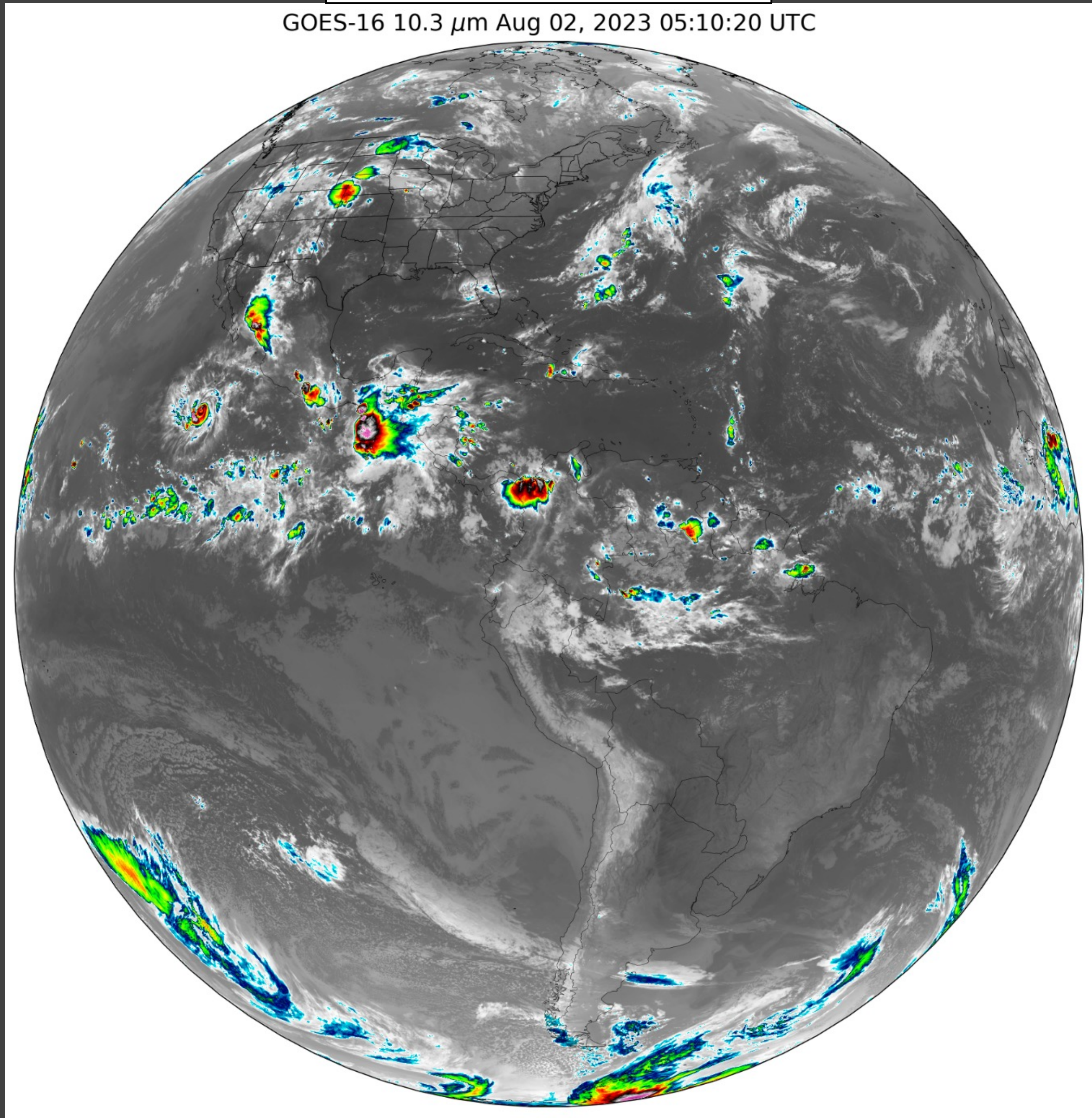
GeoColor computed downstream of interpolation, meaning city lights/terminator will not contain artifacts!

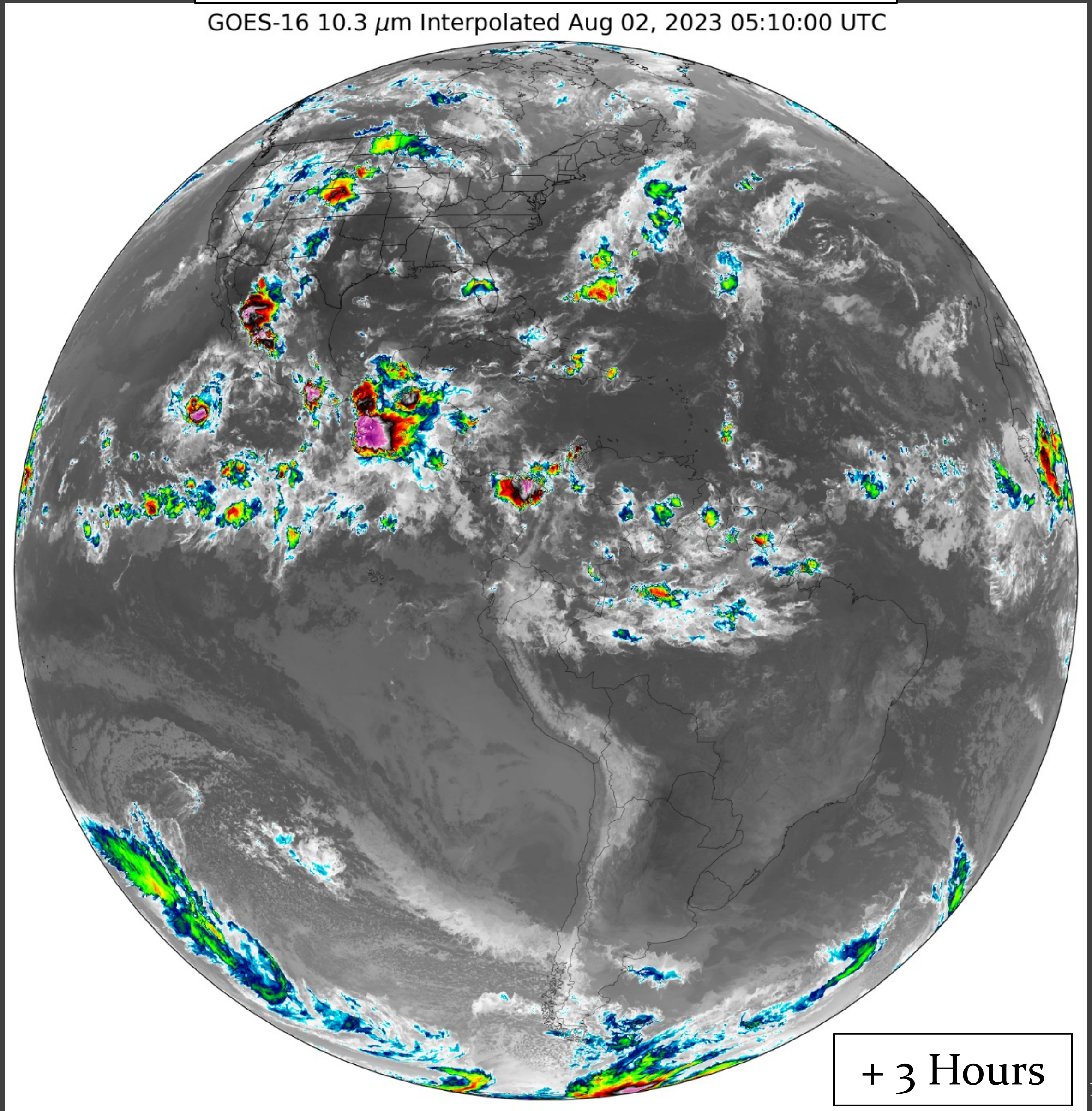



Interpolated 30 sec


Actual 30 sec

OF Nowcasting Example





UNET for 3D Nowcasting

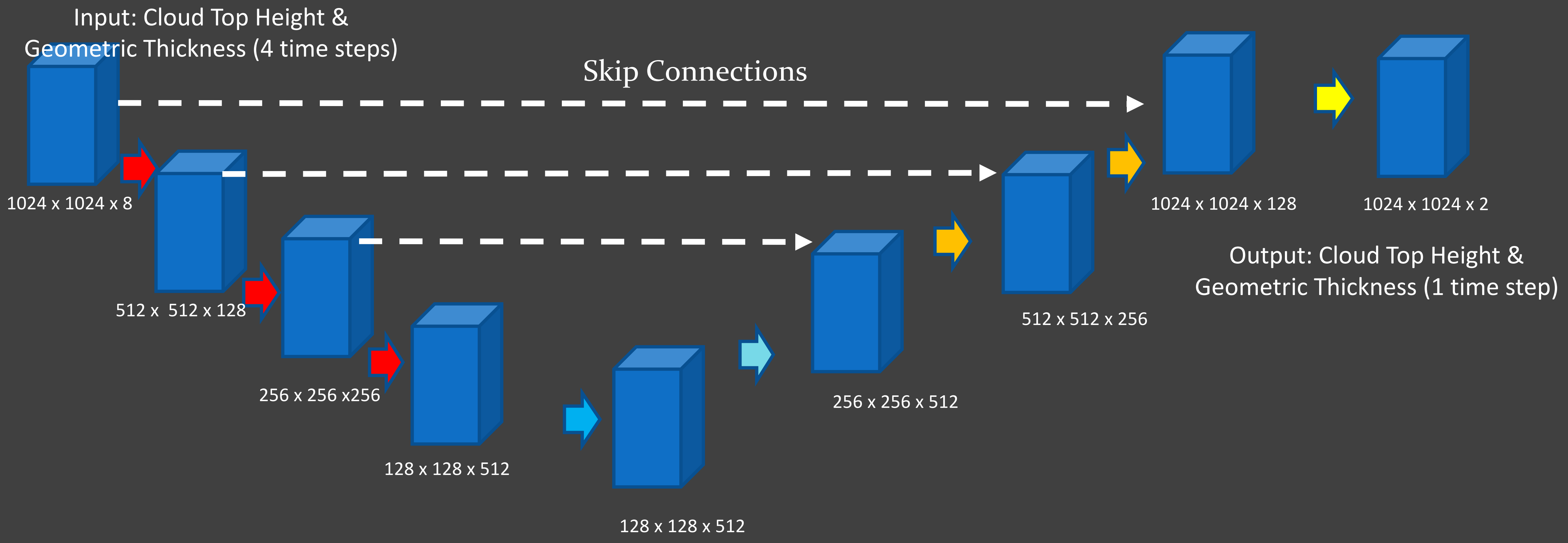
2D Depthwise Conv (3x3)
2D Conv (1x1)
2DMax Pooling (2x2)
ReLU Activation

2D Depthwise Conv (3x3)
2D Conv (1x1)
ReLU Activation

2D Up Sampling (2x2)

2D Depthwise Conv (3x3)
2D Conv (1x1)
2D Up Sampling (2x2)
ReLU Activation

Conv2D (3x3)



UNET Results

- 18 Mar 2023 example
  - 1 hour nowcast
  - Prediction in 5 min increments
- Trained on 1000 samples of GOES-16 CONUS CLAVR-x data
  - 5 min and then 10 min data
- Possibility that architecture is causing under-fitting
- Will need to assess better architecture that keeps time dimension separated longer

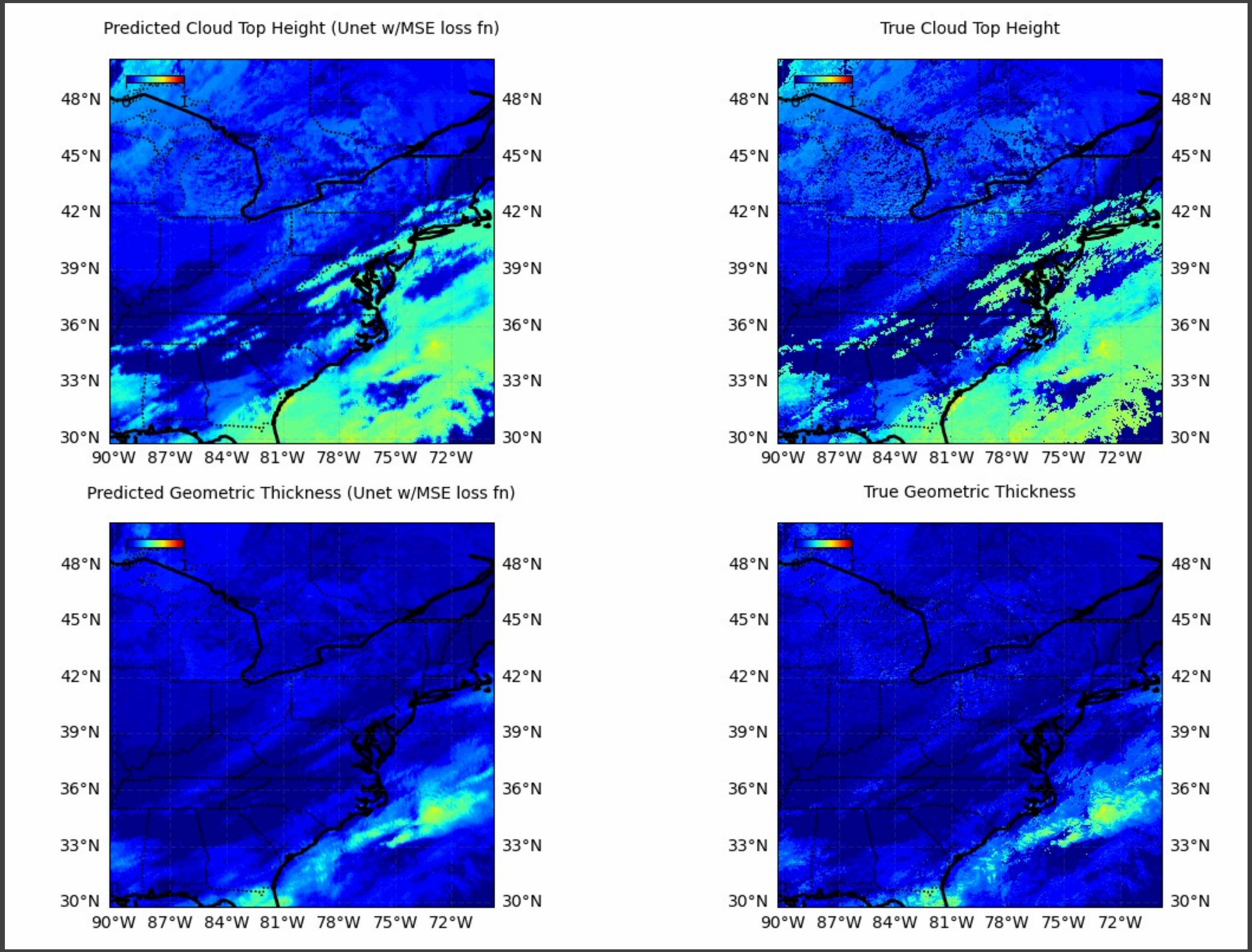


Figure 8. Early UNet results using predictions as input for subsequent predictions

Summary and Future Work

- This presentation covered the optical flow and machine learning research at CIRA to nowcast clouds
  - Optical flow and advection methods do well in areas of where clouds only, but do poorly in areas of cloud formation and dissipation
  - In regions where clouds only advect, optical flow and NWP wind-based nowcasting methods perform well
  - Both techniques struggle where formation and dissipation occurs, which we are attempting to solve with Machine Learning

Future Work:

- OCTANE and other products will be used for feature engineering on data inputs for cloud-nowcasting products, and identification of feature importance
- Will explore value of different machine learning architectures (i.e. Time distributed layers, Diffusion, LSTM, Transformers)

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Citations

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Thank You For Listening!

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