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Advances in Optical Flow Retrieval Methods for Inferring Atmospheric Winds and Motions

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Introduction

- Retrieval of brightness motions, or the Optical Flow, is a fundamental step in Atmospheric Motion Vector (AMV) derivation
- **Optical Flow Definition:**

  "The distribution of apparent velocities of movement of brightness patterns in an image" (Horn and Schunck 1981)
- Rapid scanning enables novel techniques to retrieve "Dense" (Every Image Pixel) Optical Flow for most cloud/water vapor motions
- Like a different channel on an imager, optical flow provides unique context of an image scene for a variety of users
  - ➢ NWP
  - ➢ Forecasters
  - ➢ Machine Learning/AI

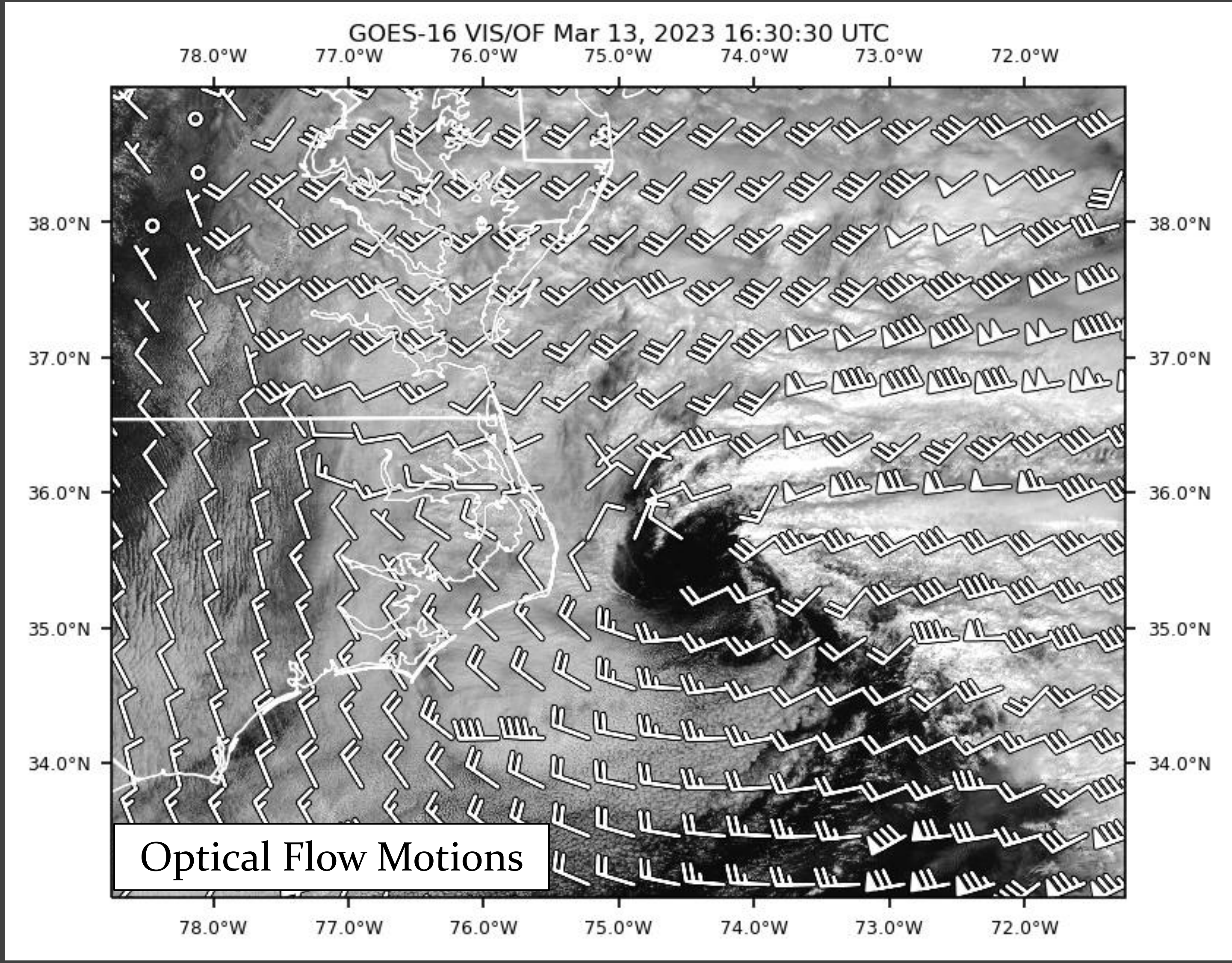


Figure 1. GOES-16 Ch-02 0.64 µm imagery plotted with optical flow winds (white barbs) over a low-pressure system of the coast of VA/NC.

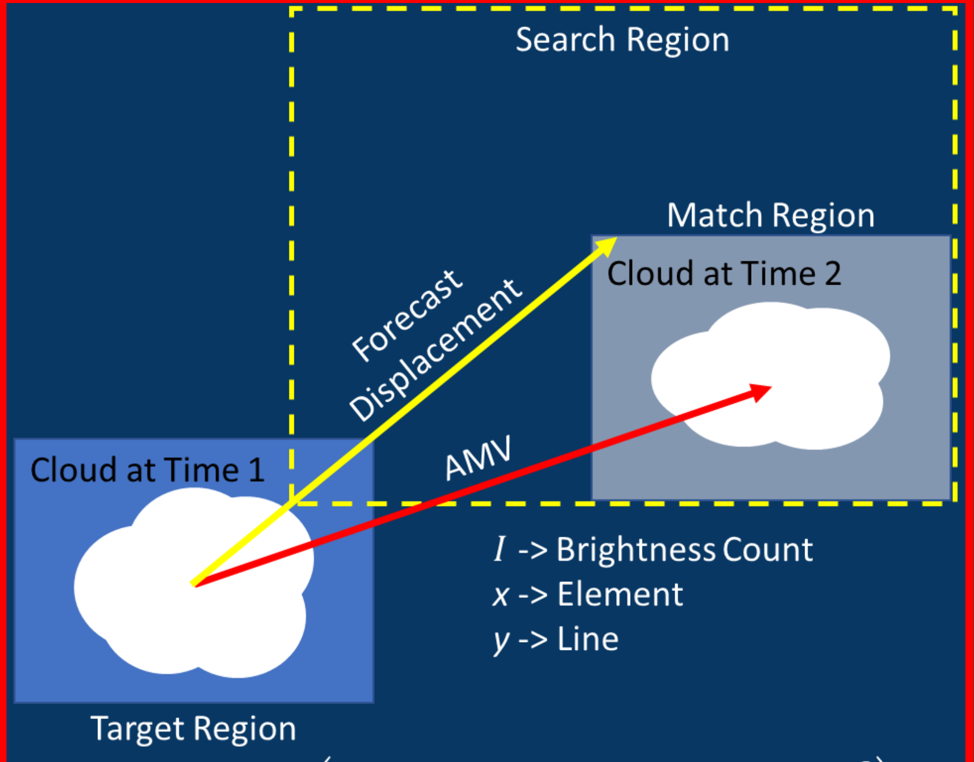
Optical Flow ≠ Winds/AMVs!

Atmospheric Motion Vectors (AMVs) are a retrieval of atmospheric winds using cloud and water-vapor drift motions

They use a 5-step "Patch Matching" method

1. Identify target in VIS/IR/WV Imagery
2. Height Assign target with Numerical Weather Prediction (NWP) Fields to Forecast Displacement
3. Identify the target in next image w/ least-squares/cross-correlation
   - GOES-R algorithm clusters tracked results over a larger target area
4. Navigate results from pixel displacements to m s^{-1} / Refine Height Assignment
5. Implement quality control to prune results or provide meaningful error info

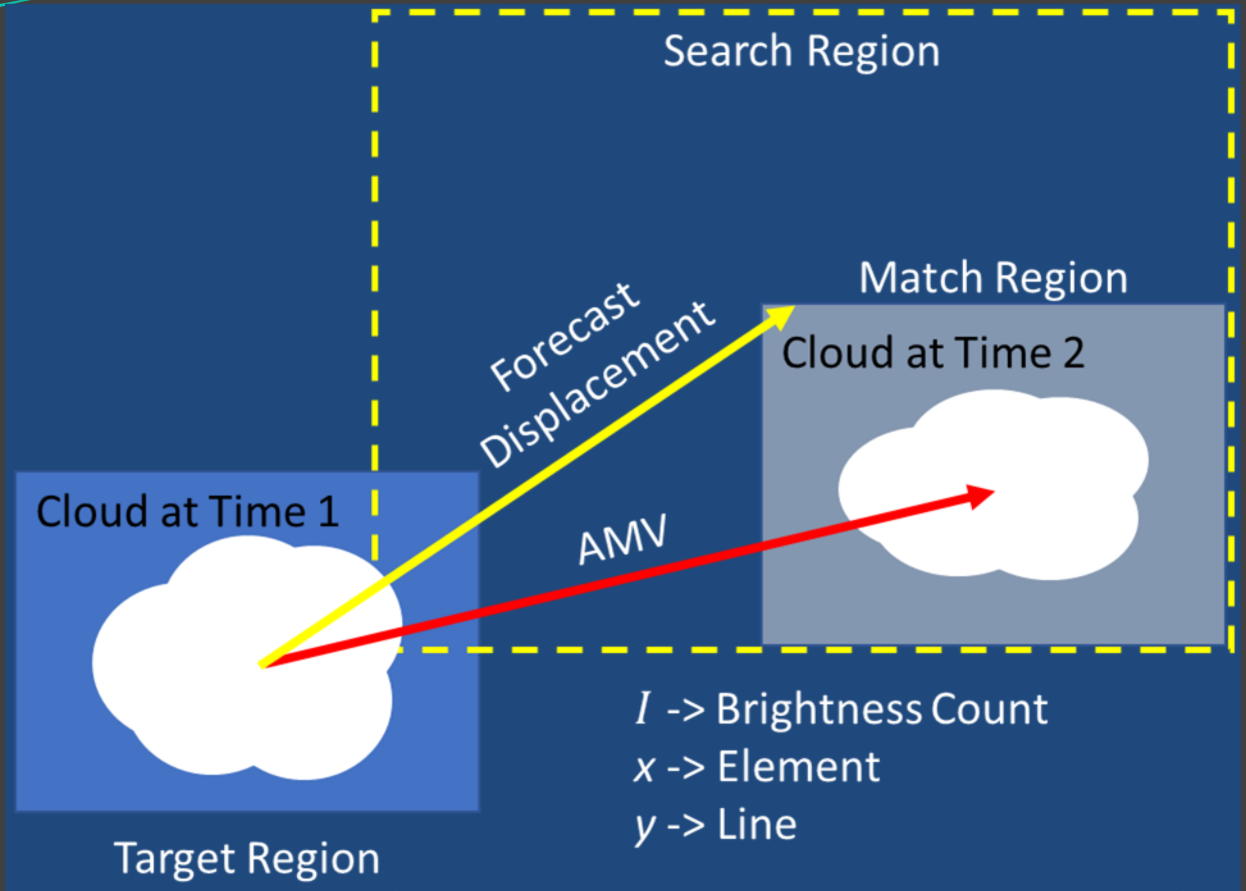
The Optical Flow Retrieval Step



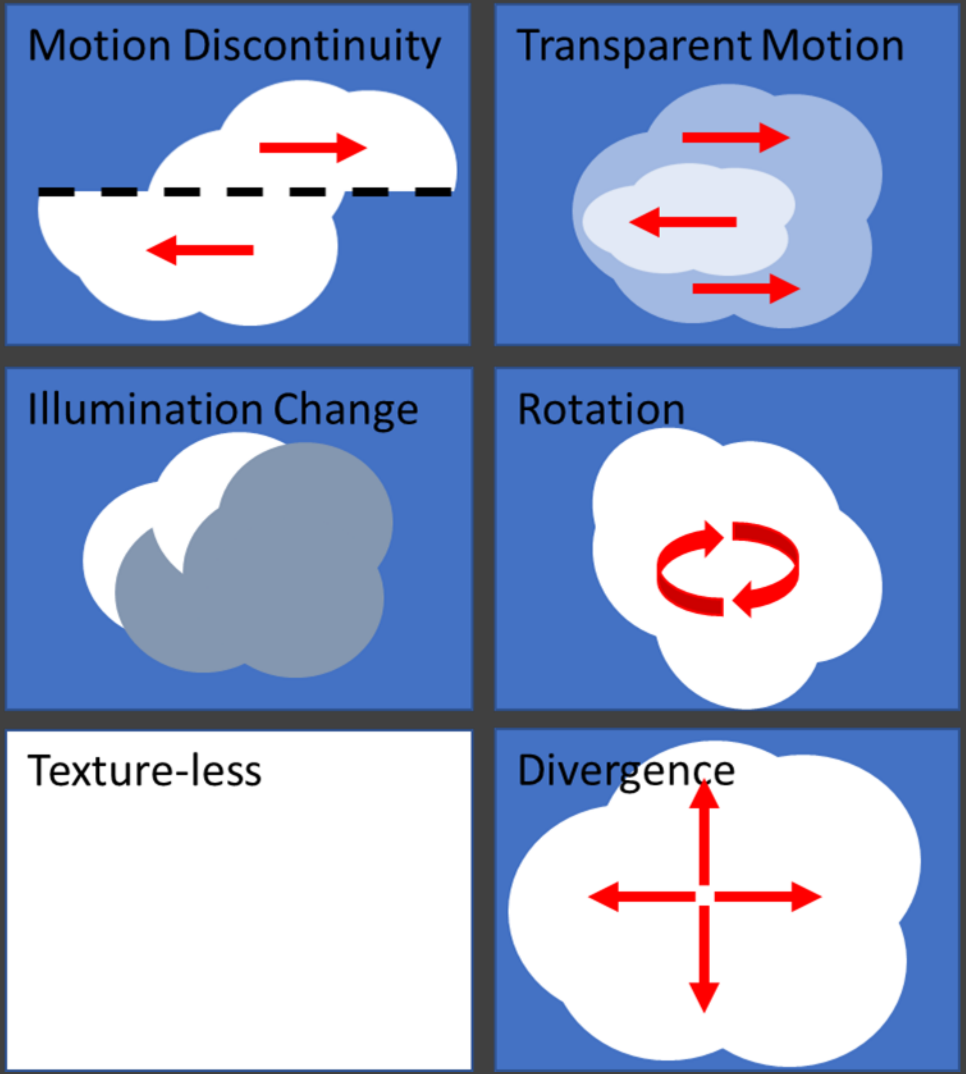
$$Match = \min\left(\sum_{x,y}\left(I_{target}(x,y) - I_{search}(x,y)\right)^2\right)$$

Figure 2. Schematic of Atmospheric Motion Vector optical flow derivation. In practice, this is performed twice, forwards (like that shown above) and backwards in time, and the two AMVs are used for quality control and then averaged to produce a final motion estimate (Adapted from Bresky et al. 2012).

Pitfalls of Patch Matching



$$Match = \min\left(\sum_{x,y}\left(I_{target}(x,y) - I_{search}(x,y)\right)^2\right)$$



This approach fails if → Any one of these happen

*Operational AMVs are VERY GOOD at finding/pruning bad targets, final winds product is "Sparse", meaning only some pixels have wind solutions. Dense motions must account for these difficult to track regions!

OCTANE

Connecting Models and Observations

- OCTANE: **O**ptical flow **C**ode for **T**racking, **A**tmospheric motion vector, and **N**owcasting **E**xperiments (Developed under ONR funding from "MURI" & "RAM-HORNS"; PI: Steve Miller) (also see Apke and Mecikalski 2021)
- Inputs: Satellite image sequences/pairs (NetCDF), Outputs: Dense optical flow displacements (NetCDF)
- Output can be x- and y- pixel displacements or navigated zonal/meridional motion (m s^{-1})
- Includes GPU-accelerated variational optical flow retrieval algorithms, (e.g. Zimmer et al. 2011):

$$E(\boldsymbol{U}) = \iint_{\Omega} \rho_d(BC + \gamma\ GC) + \alpha\ \rho_s(SC) d\boldsymbol{x}$$

$I \rightarrow Image, \boldsymbol{U} \rightarrow Optical\ Flow\ Vector, t \rightarrow time$

$x \rightarrow location\ vector, I_{x,y} \rightarrow image\ x,y\ derivative$

BC = Brightness Constancy -> $C_1\ |I(\boldsymbol{x}+\boldsymbol{U}, t+\Delta t) - I(\boldsymbol{x},t)|^2$

GC = Gradient Constancy -> $|C_2(I_x(\boldsymbol{x}+\boldsymbol{U}, t+\Delta t) - I_x(\boldsymbol{x},t))|^2 + |C_3(I_y(\boldsymbol{x}+\boldsymbol{U}, t+\Delta t) - I_y(\boldsymbol{x},t))|^2$, γ = weight of GC

SC = Smoothness Constraint -> $|\nabla u|^2 + |\nabla v|^2$, α = weight of SC

The $\rho_d(x^2) = \rho_s(x^2) = \sqrt{x^2+\varepsilon^2}$ are "Robust Functions", and $C_1 = \frac{1}{|\nabla I|^2+\epsilon}$ and $C_2 = \frac{1}{|\nabla I_x|^2+\epsilon}$ and $C_3 = \frac{1}{|\nabla I_y|^2+\epsilon}$

Mitigates motion caused by illumination changes & preserves discontinuities

- Variational OF retrieval uses intuitive methods to track ordinarily difficult regions, such as those without texture, or with illumination changes, deformations, and discontinuities
- Constants/Constraints can be modified for different applications
- GPU acceleration enables practical real time computation
- Code for OCTANE is now on GITHUB: https://github.com/JasonApke/OCTANE

Tuning for Winds Retrieval

- OCTANE approaches are tuned with ancillary samples of tropospheric winds (e.g. lidar wind profilers)
- Winds are benchmarked by filling columns along the Lidar track with estimates from AMV products
  - Challenges both tracking AND height assignment!
  - Encourages dense multi-layer winds solutions
  - Benchmarks techniques with one clean score (Root mean square vector difference)

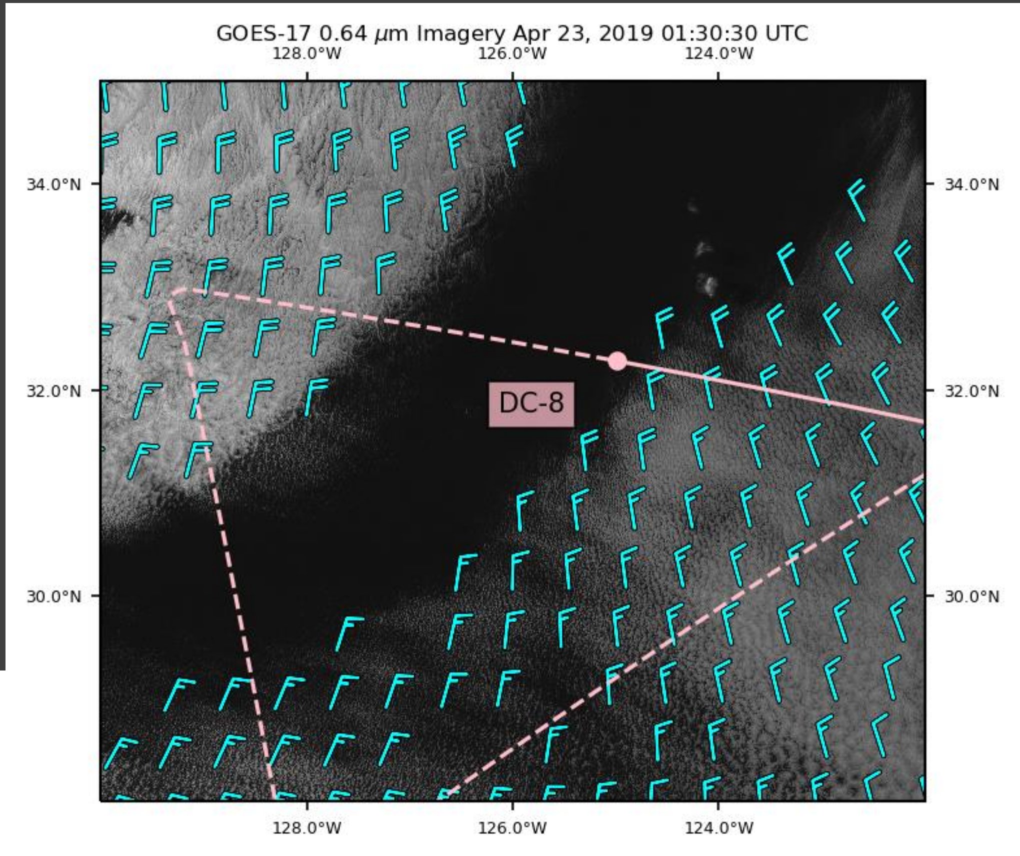
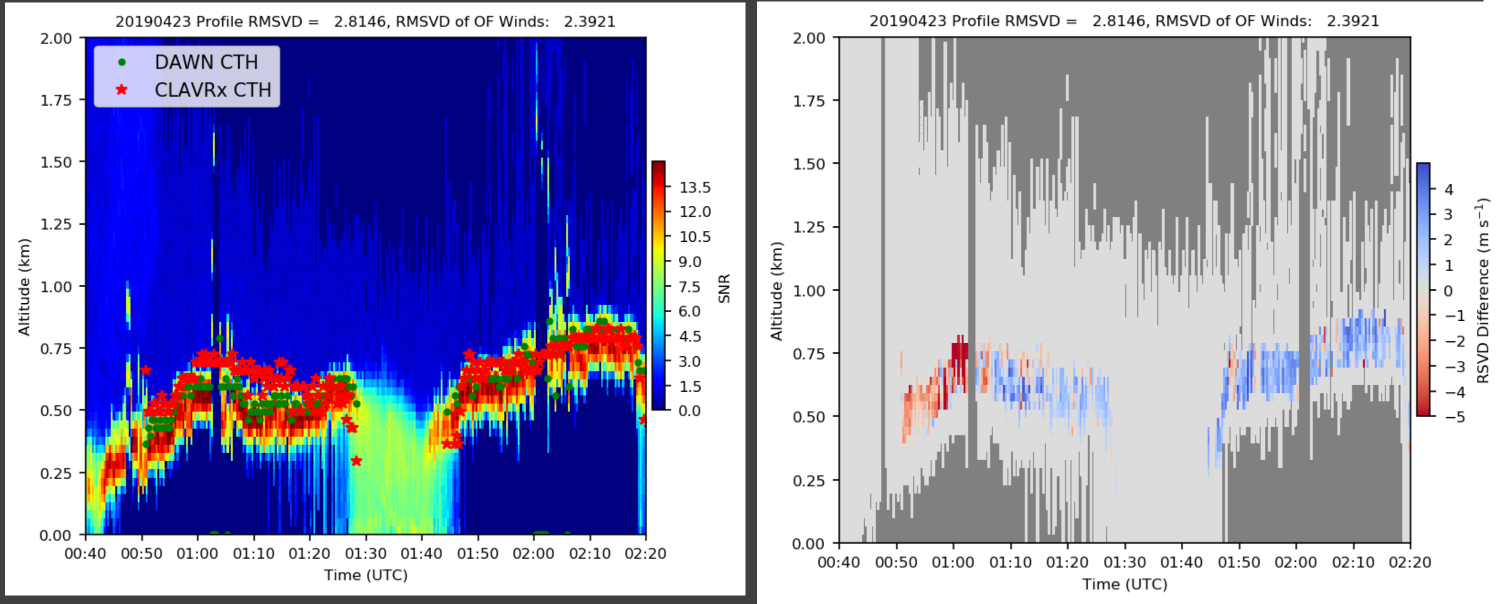


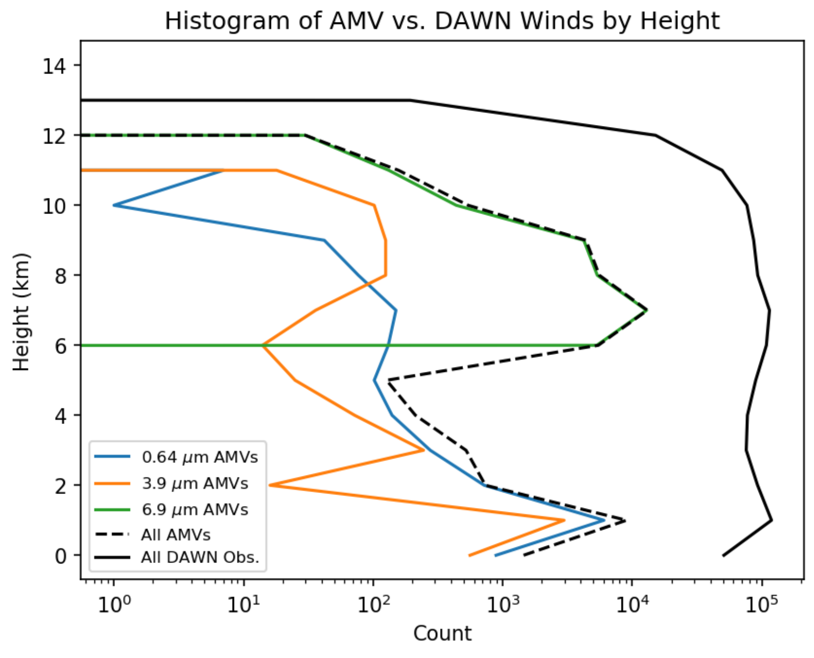
Figure 3. GOES-17 Ch-02 0.64 μm imagery plotted with 1-min DOF, shown with the past (future) track of the NASA DC-8 carrying the DAWN wind profiler in pink (pink dash).

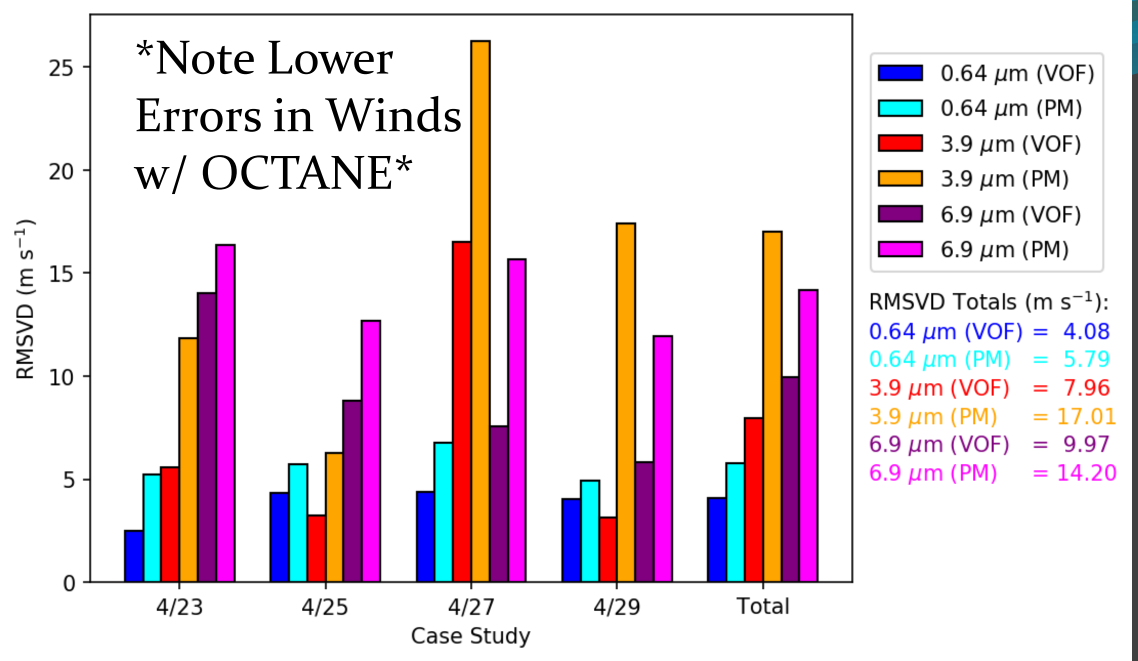
Figure 2. (*Left*) Wind profiling Lidar (DAWN) Signal-to-noise ratio and cloud-top heights (shading/green circles) compared to DOF/NOAA Enterprise cloud-top heights (CLAVRx) along the track of the NASA DC-8. (*Right*) DOF wind estimate improvement (m s^{-1}) over a model background guess of the wind profile, with improvements (deteriorations) shown in blue (red).



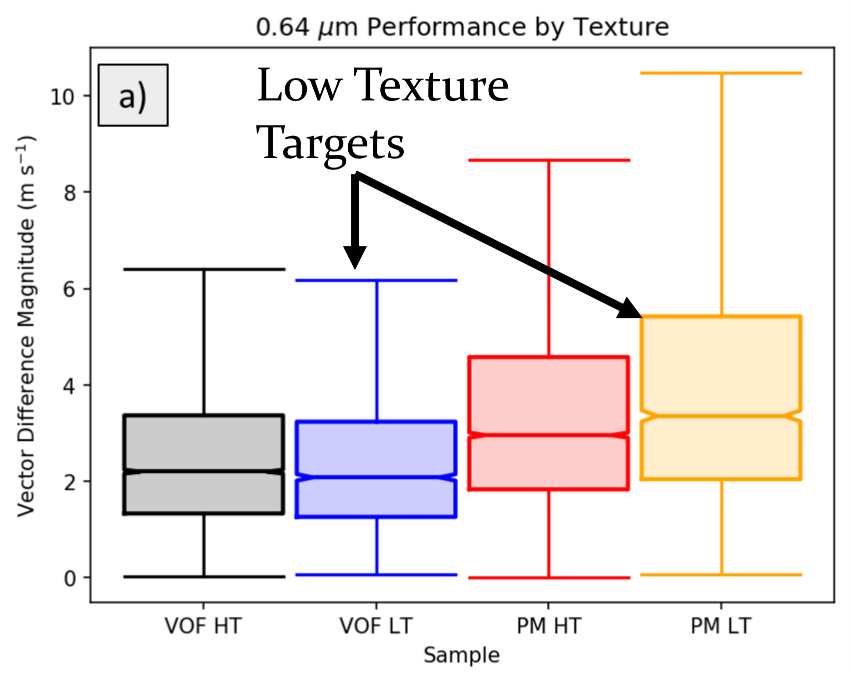
Bedka, K. M., Nehrir, A. R., Kavaya, M., Barton-Grimley, R., Beaubien, M., Carroll, B., Collins, J., Cooney, J., Emmitt, G. D., Greco, S., Kooi, S., Lee, T., Liu, Z., Rodier, S., & Skofronick-Jackson, G. (2021). Airborne lidar observations of wind, water vapor, and aerosol profiles during the NASA Aeolus calibration and validation (Cal/Val) test flight campaign. *Atmospheric Measurement Techniques*, **14**(6), 4305–4334. https://doi.org/10.5194/amt-14-4305-2021

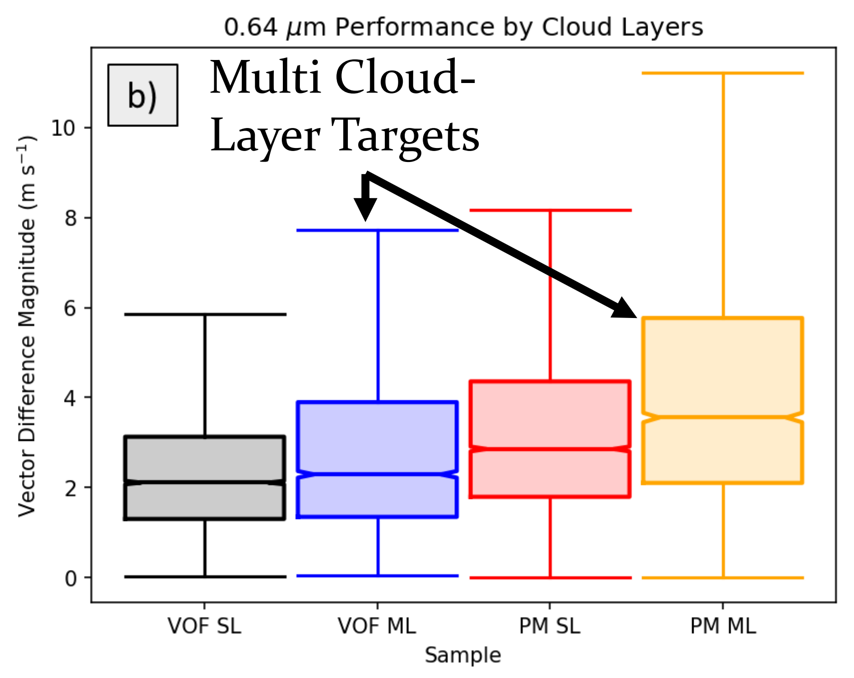
Figure 4. (*Top left*) Benchmark sample of AMVs and wind-profiling lidar truth winds by height and by channel used. (*Top Right*) Root mean squared vector difference for AMVs derived with different methods and imager channels. (*Bottom left*) Vector differences of AMVs derived with 0.64 µm imagery separated by high and low texture (HT and LT), and (*Bottom right*) single- and multi-layer (SL and ML) cloud targets.





- OCTANE (abbreviated VOF here) produces lower errors than patch matching (PM), used in operational AMVs), in Low Texture (LT) and multi-layer (ML) Targets
- Benchmarking results indicate OCTANE can be used to resolve winds where operational AMVs break down***

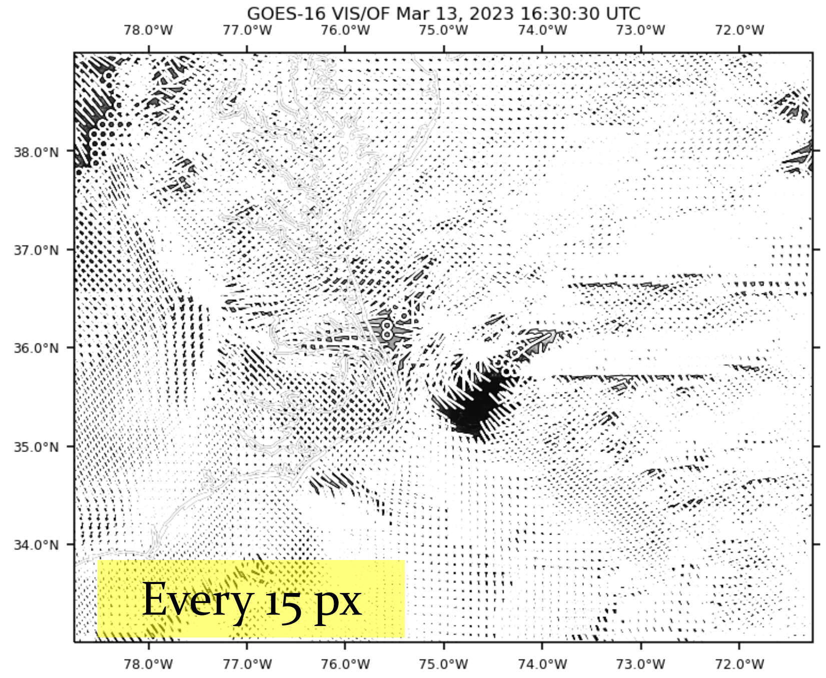


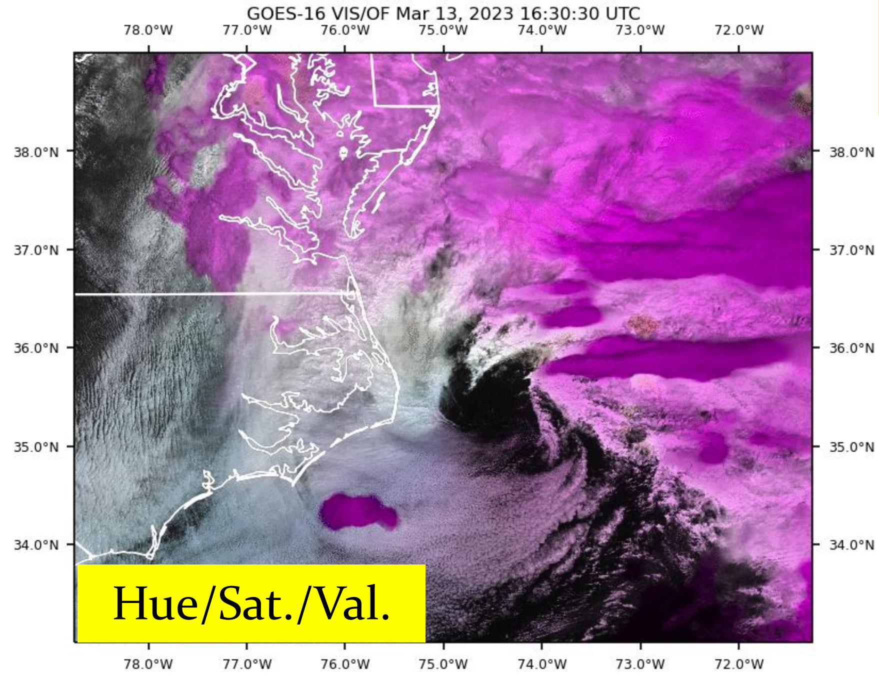


Apke, J. M., Y.-J. Noh, and K. Bedka, 2022: Comparison of Optical Flow Derivation Techniques for Retrieving Tropospheric Winds from Satellite Image Sequences. *J Atmos Ocean Technol,* **39**, 2005–2021, https://doi.org/10.1175/jtech-d-22-0057.1.

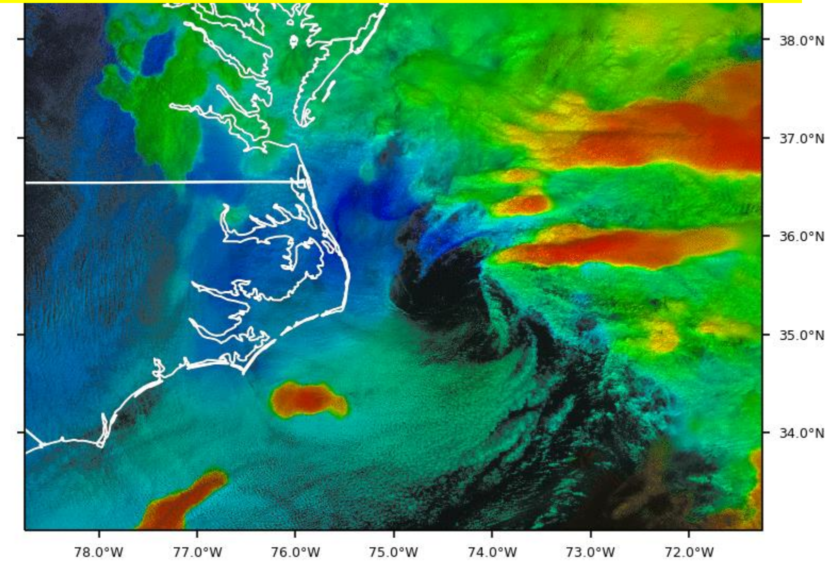
Plotting Dense OF-based AMVs

Barbs (Conventional)	Color Shaded Speed/Direction	Speed/Imagery Blends (Exp.)



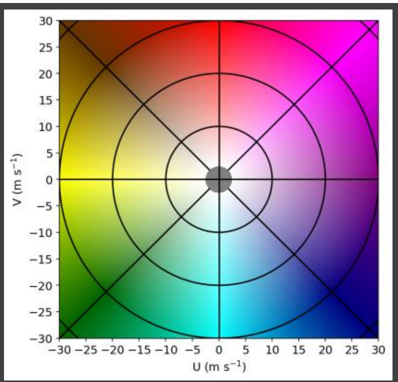


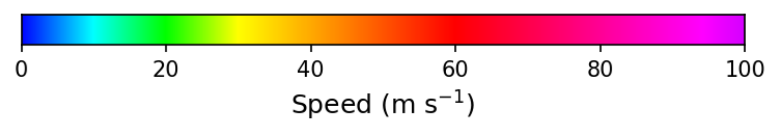
Produced in NRT on CIRA SLIDER, uses 0.64 µm during the day, 10.3 µm at night



Advantage:
Interpretability
Disadvantages:
Cannot highlight dense motions
Noisy with slower motions

Advantages:
Highlights dense motions, edges, and directional changes
Disadvantages:
Ambiguous for wind speeds

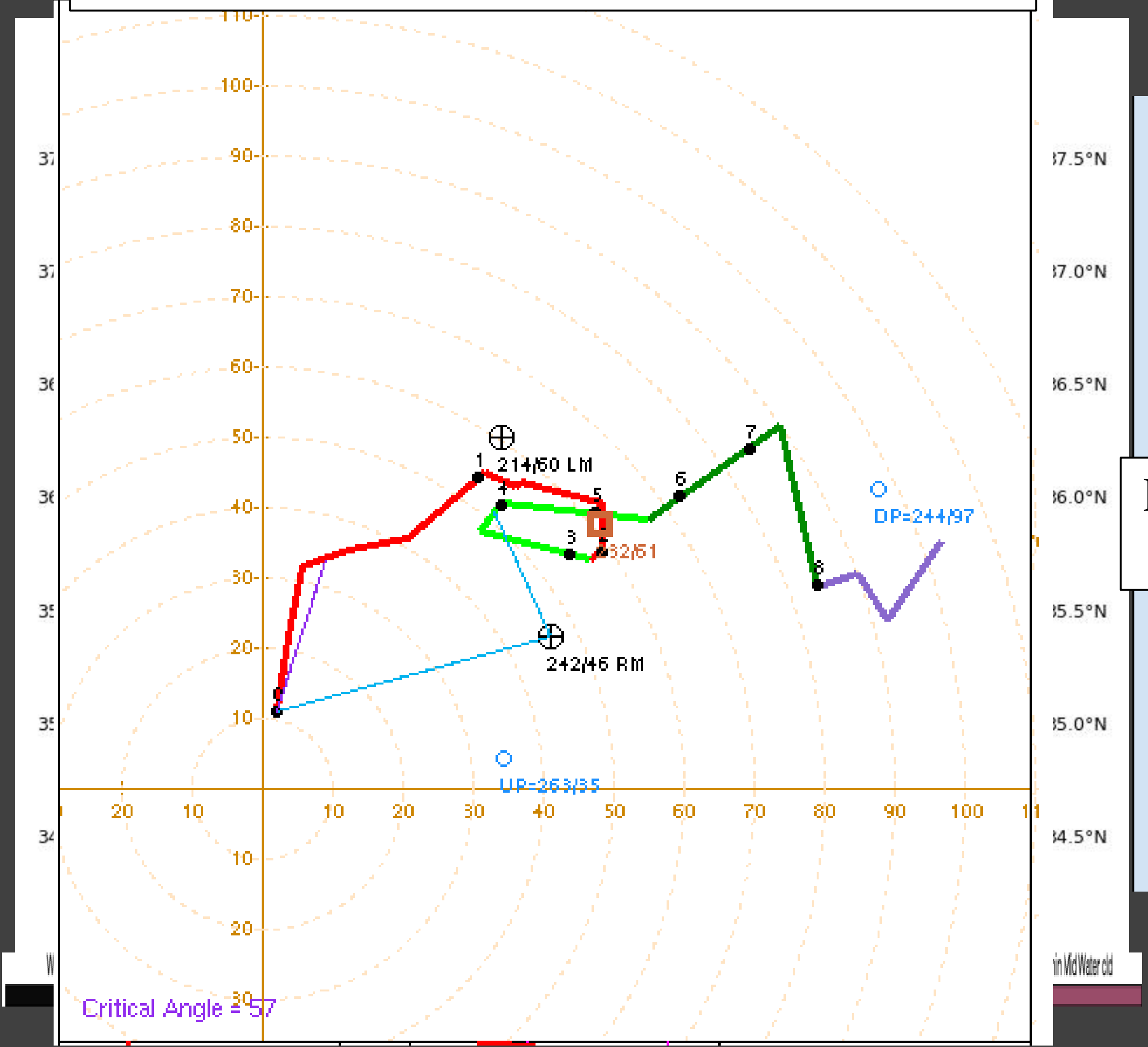




Advantages:
Highlights dense speeds and features producing motions, Interpretability
Disadvantages:
Ambiguous for direction

Speed Sandwich (CI in High Shear)

18 Z Sounding from Little Rock, AR (Red Star)



DOF Speed/Visible "Sandwich"

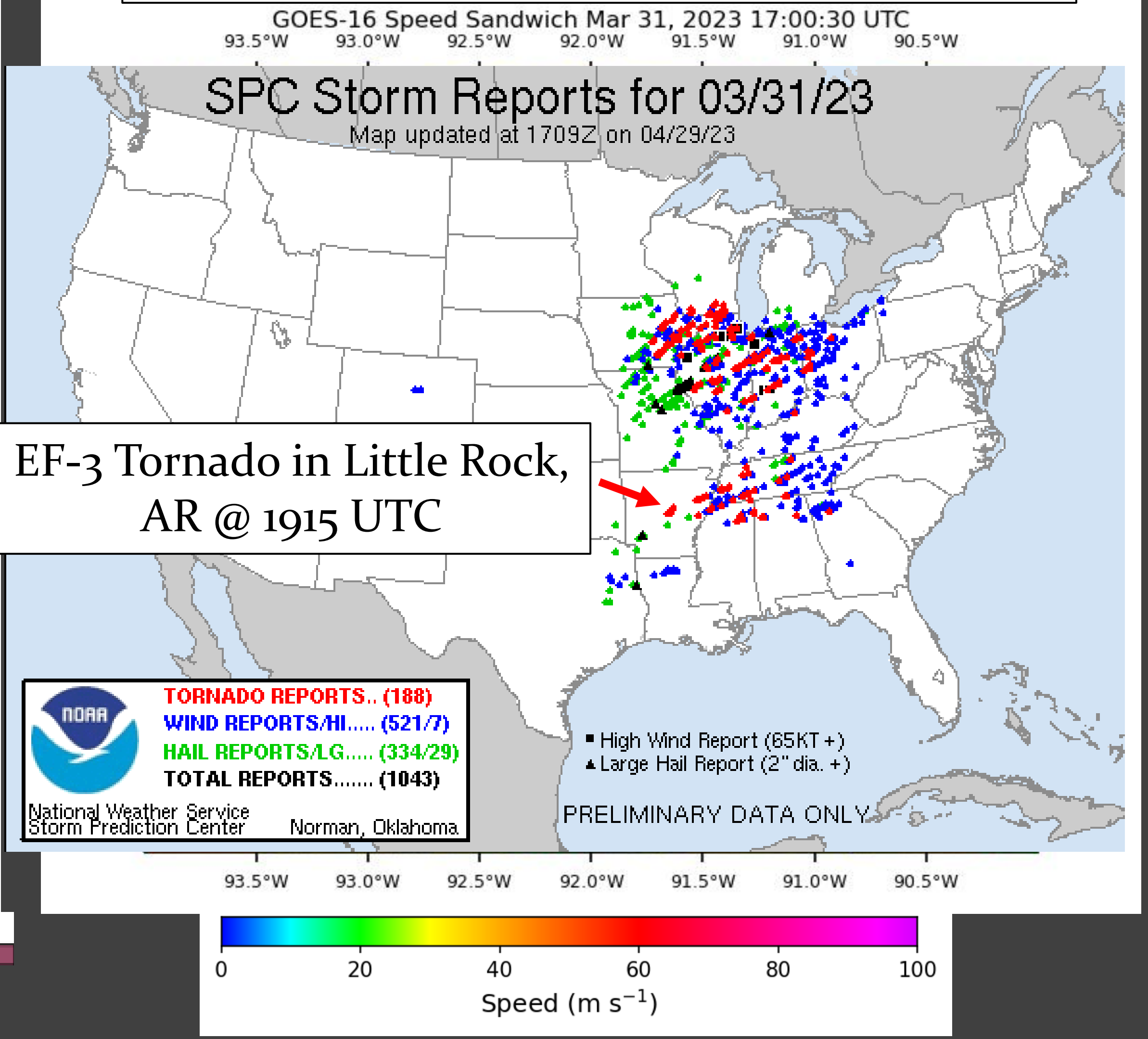
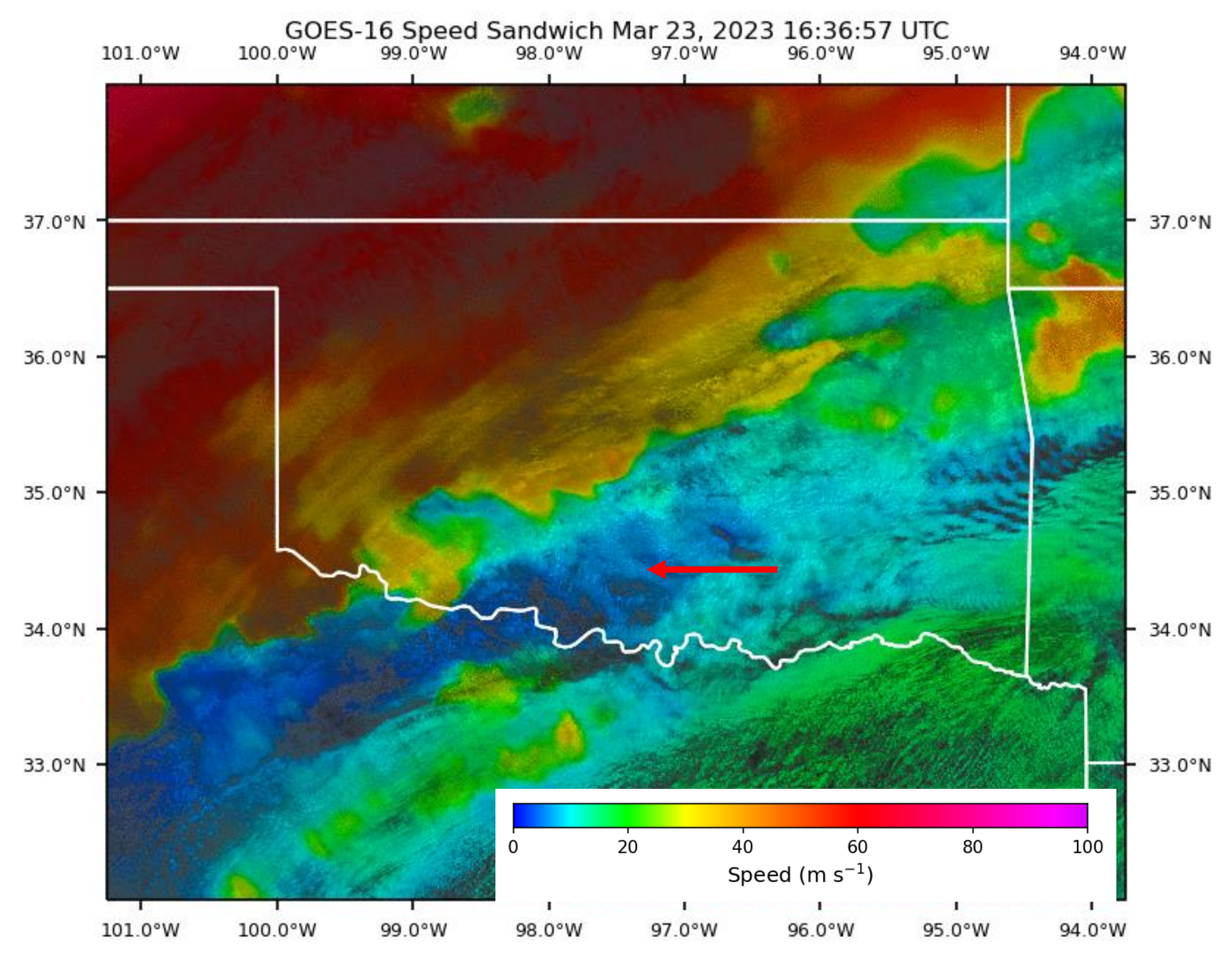


Figure 4. (*Left*) GOES-16 Day-Cloud Phase enhancement (from 0.64, 1.6, and 10.3 μm imagery) shown with (*Right*) Dense optical flow colored by wind speed with brightness indicating the 0.64 μm reflectance (The Speed Sandwich product).

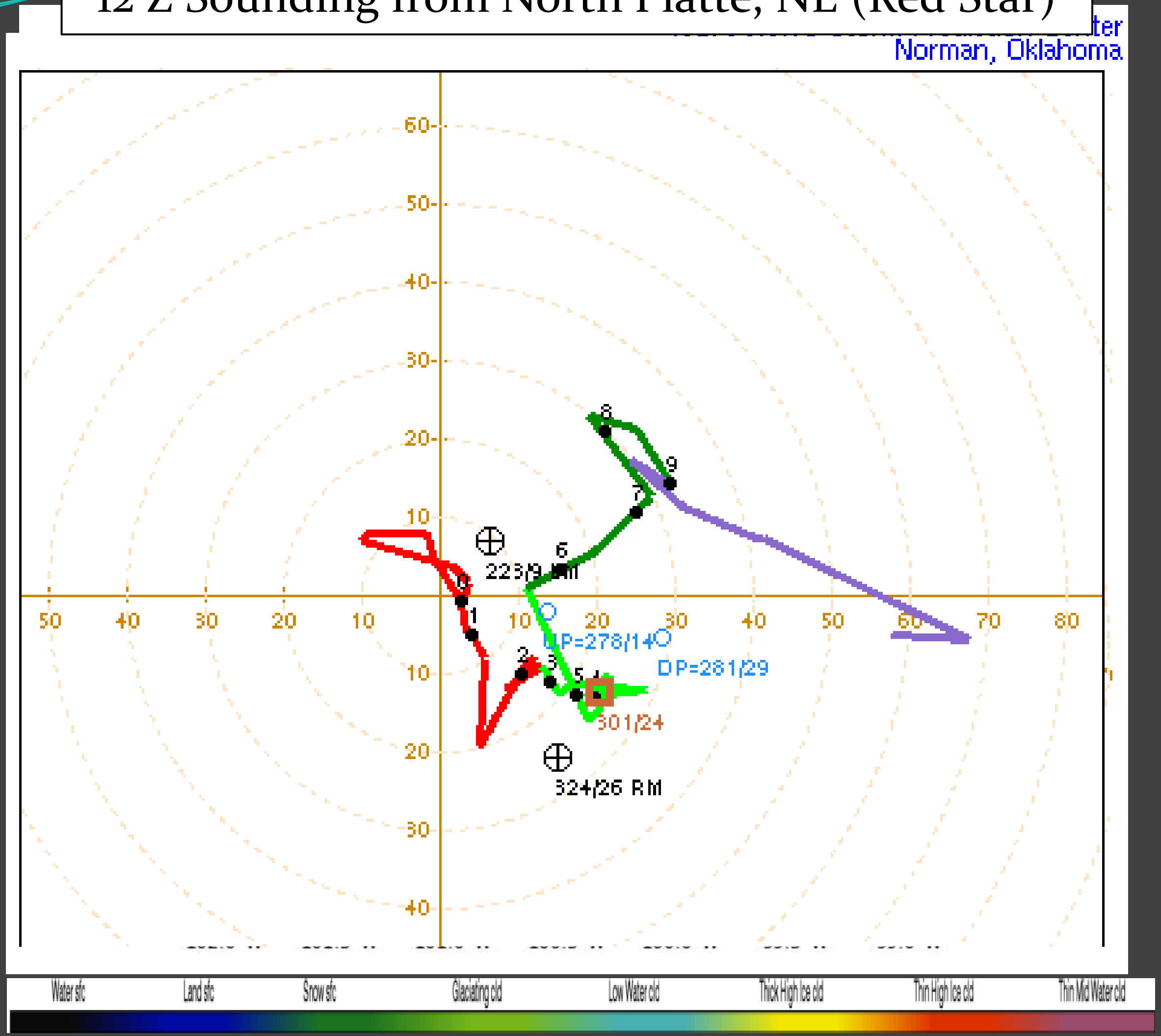
Speed Sandwich (Mesoscale Ascent)

- In some examples w/ strong low-level shear, OCTANE motions can highlight regions of mesoscale ascent
- Notice the faster motions that formed in advance of the boundary several hours in advance of CI!
- Notice that it sees the motion acceleration beneath thin cirrus!



Speed Sandwich (CI in Low Shear)

12 Z Sounding from North Platte, NE (Red Star)



DOF Speed/Visible "Sandwich"

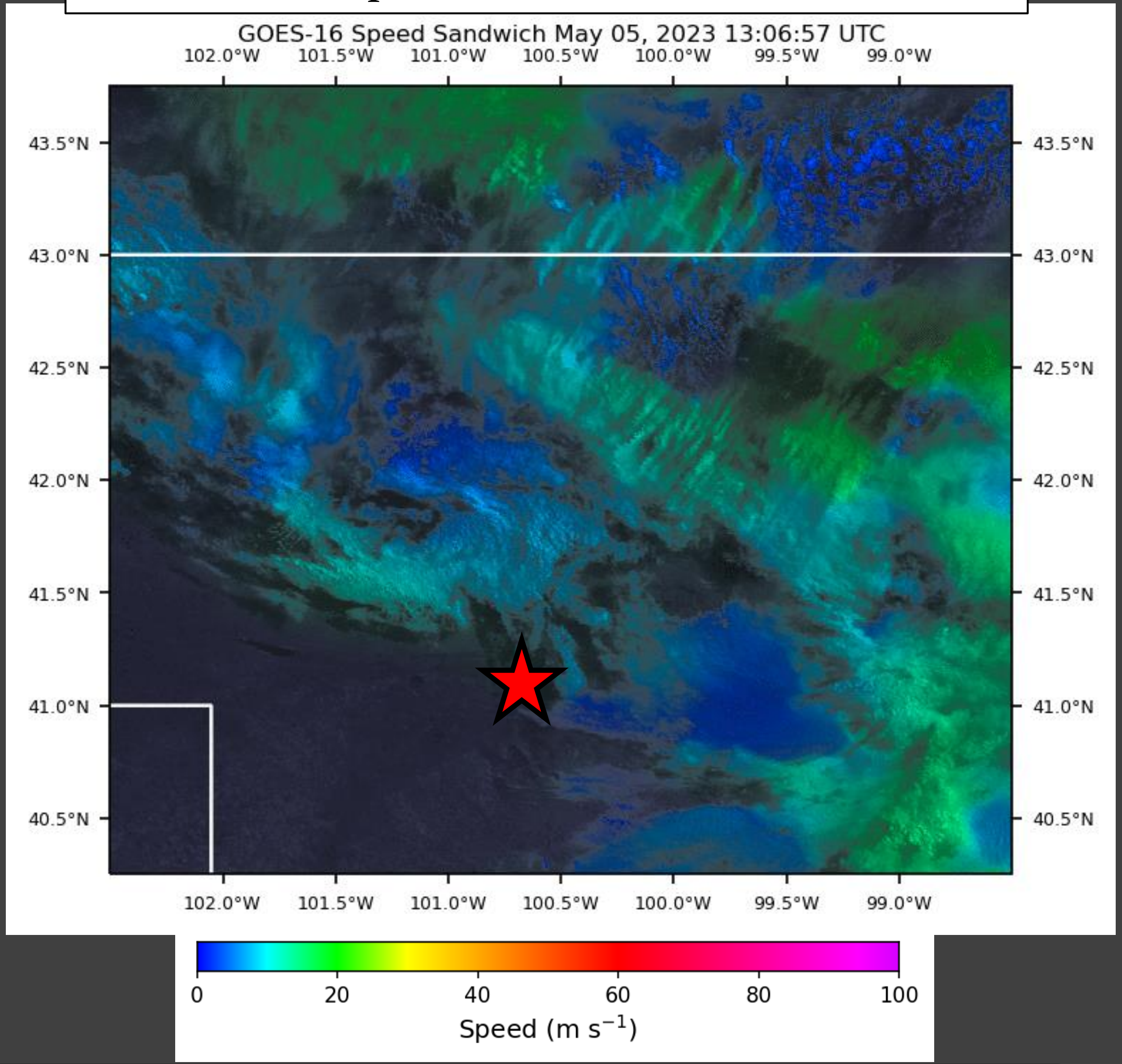


Figure 5. (*Left*) GOES-16 Day-Cloud Phase enhancement (from 0.64, 1.6, and 10.3 µm imagery) shown with (*Right*) Dense optical flow colored by wind speed with brightness indicating the 0.64 µm reflectance (The Speed Sandwich product).

AIRWOLF

- OCTANE provides noteworthy capabilities for difficult to track scenes, but still has limited performance in low texture and transparent motions, and motions w/ very large displacements
- It is also challenging to properly height assign regularized dense OF motions
- One possible solution to further enhance OF retrieval is via AI/Machine Learning
- CIRA is working on the Artificial Intelligence-based Retrieval of Winds using OpticaL Flow (AIRWOLF) project to develop such systems

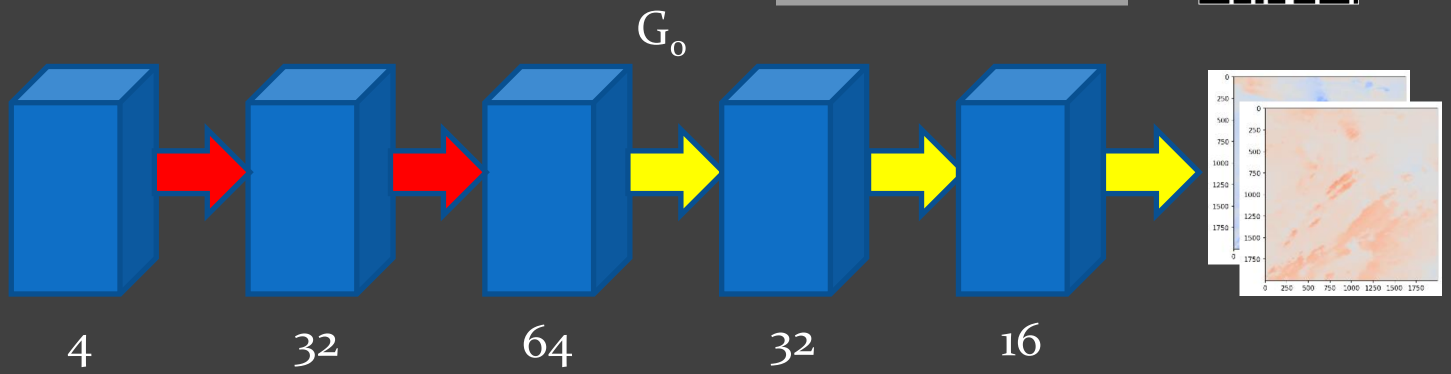
Table 1. AIRWOLF development parameter settings.

Parameter	Setting
Truth Dataset	OCTANE x/y displacements
Inputs	2 1-min 0.64 µm images
Training Sample Size	2432 Image Pairs
Training Times	Aug-Sept 2022
Training Interval	Pairs every 5-min
Testing Sample Size	512 Image Pairs
ML Library	PyTorch
Loss Function	L1 Flow Distance/EPE
Optimizer	Adam
Learning Rate	1×10^{-4}
Batch Size	128
Epochs (lvl 1 / lvl 2 / lvl 3)	4000 / 250 / 250

AIRWOLF Architecture (SPYNET)

Conv2D 7x7 S-1, Leaky RELU

Conv2DTrans 7x7 S-1, Leaky RELU



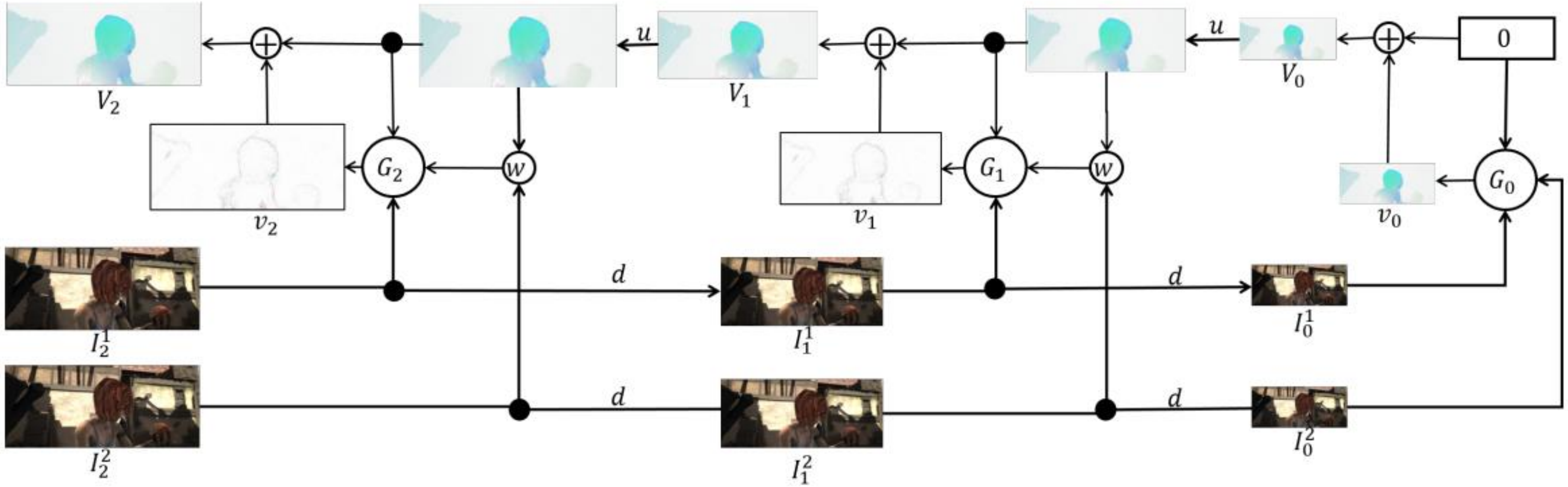


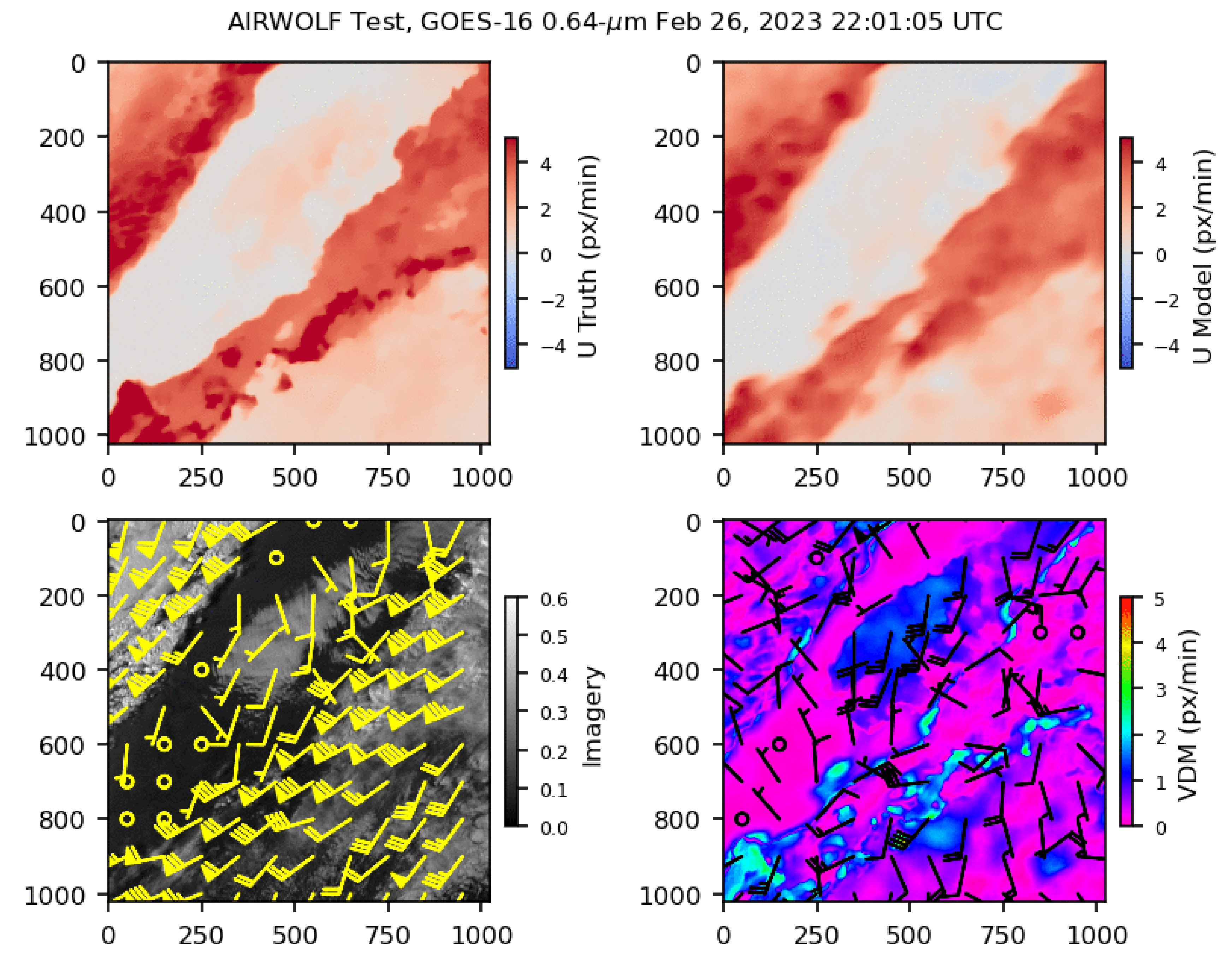
Figure 1. Inference in a 3-Level Pyramid Network [15]: The network G_0 computes the residual flow v_0 at the highest level of the pyramid (smallest image) using the low resolution images $\{I_0^1, I_0^2\}$. At each pyramid level, the network G_k computes a residual flow v_k which propagates to each of the next lower levels of the pyramid in turn, to finally obtain the flow V_2 at the highest resolution.

Key:
G -> CNNs
d -> down-sampling
u -> up-sampling
w -> warping
V -> flow at each level

Source of Images: Ranjan, A. and M. J. Black, 2017: Optical Flow estimation using a spatial pyramid network. *IEEE Conference on Computer Vision and Pattern Recognition (CVPR). https://arxiv.org/pdf/1611.00850.pdf*

Early Results

- AIRWOLF when trained on OCTANE vectors shows a close correspondence to more computationally expensive optical flow
- Less sensitive to thin cirrus (may be useful for some applications)
- Does not resolve mesoscale motions atop convection very well so far
- Largest differences seen near cloud edges/boundaries and near cirrus



AIRWOLF vs. OCTANE- Speed Sandwich

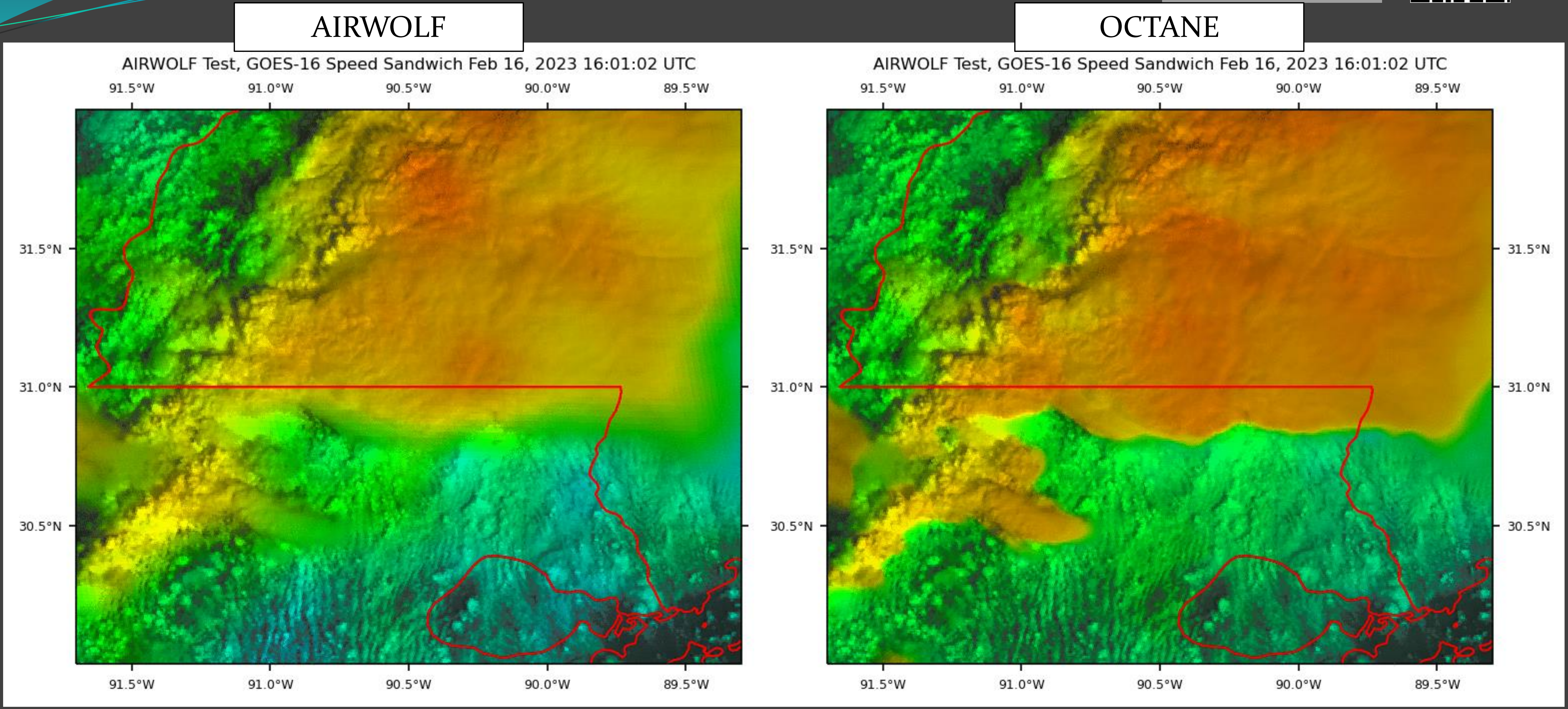


Figure 6. (*Left*) Speed Sandwich product computed using the AIRWOLF retrieved motions compared to (*Right*) computations using the OCTANE product shown over strong convection in southern MS/eastern LA on 16 Feb 2023.

Summary and Future Work

- This presentation highlighted the OCTANE and AIRWOLF products for inferring winds in the atmosphere, which offer accurate tracking where operational AMVs break down
- Overviewed simple methods for plotting dense winds with satellite imagery
- Highlighted how speed/imagery blends can be useful for convective forecasting

Future Work:

- OCTANE winds products are now in AWIPS, will be demonstrated at the 2023 Hazardous Weather Testbed and evaluated by forecasters
- OCTANE cloud-top divergence products are also under development to better highlight mature thunderstorm updrafts
- AIRWOLF development will continue, with efforts to improve outputs/reduce noise, including increasing the training data size, modifying the architecture, and testing different loss functions to better penalize cloud motions
- AIRWOLF will be benchmarked using the method within Apke et al. (2022)
- Plans are underway to expand AIRWOLF to different channels and lower temporal resolution imagery, along with testing different truth datasets (e.g. synthetic clouds)

Acknowledgements

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Citations

Apke, J. M., & Mecikalski, J. R. (2021). On the Origin of Rotation Derived from Super Rapid Scan Satellite Imagery at the Cloud-Tops of Severe Deep Convection. *Monthly Weather Review,* **149**(6), 1827–1851. https://doi.org/10.1175/mwr-d-20-0209.1

---, Y.-J. Noh, and K. Bedka, 2022: Comparison of Optical Flow Derivation Techniques for Retrieving Tropospheric Winds from Satellite Image Sequences. *J Atmos. Ocea. Tech.,* **39,** 2005–2021, https://doi.org/10.1175/jtech-d-22-0057.1.

Zimmer, H., A. Bruhn, and J. Weickert, 2011: Optic flow in harmony. *Int. J. Comput. Vis.*, **93**, 368–388, doi:10.1007/s11263-011-0422-6.

Thank You For Listening!

Presentation Here

Realtime on SLIDER

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