Estimating Optical Flows in Satellite Imagery

Working Group Meeting for Space Lidar Winds

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NASA Earth Exchange

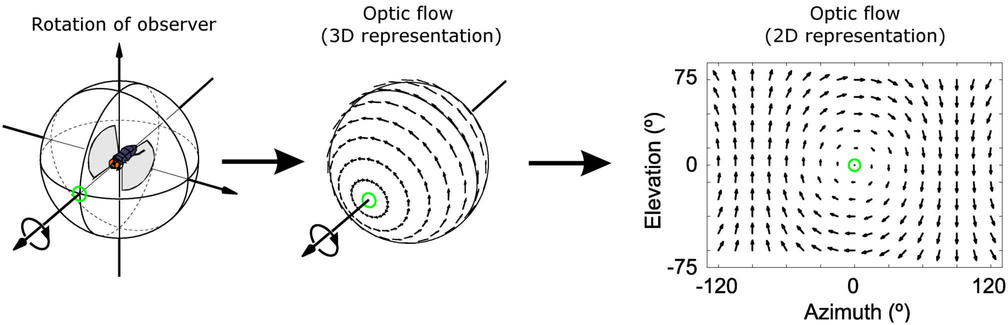
Roadmap

Introduction to Optical Flow

Introduction to Optical Flow

Optical Flow is the distribution of apparent velocities of movement of brightness patterns in an image. [Horn and Schunck, 1981]

Arises from the relative movement of an object from a viewer.



Optical Flow Assumptions

Let $E(x, y, t)$ denote the brightness of pixel (x, y) at time t in a sequence of 2D images.

Assume the brightness of a particular point is constant, $\frac{dE}{dt} = 0$

Using the chain rule,

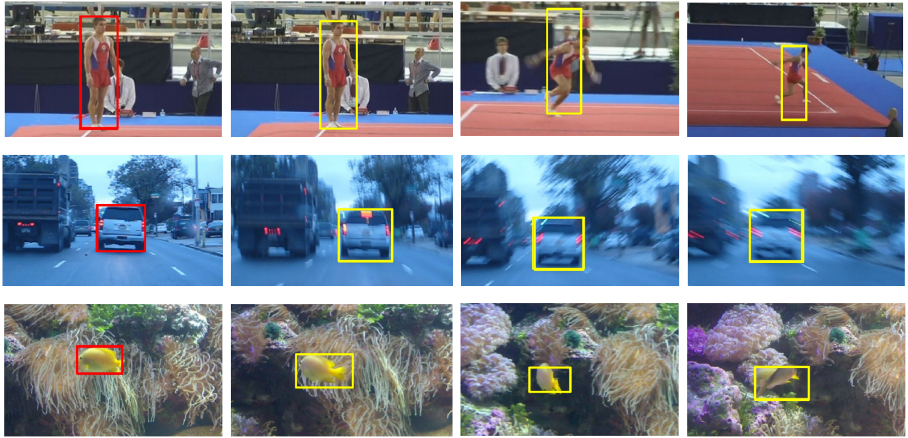
$$\frac{\partial E}{\partial x}\frac{dx}{dt} + \frac{\partial E}{\partial y}\frac{dy}{dt} + \frac{\partial E}{\partial t} = 0 \quad (1)$$

The goal is to estimate the velocities in the x and y directions: $\frac{dx}{dt}$ and $\frac{dy}{dt}$

Derivatives can be estimated using sequential images with numerical approximations.

Application I: Object Tracking [Bertinetto et al., 2016]

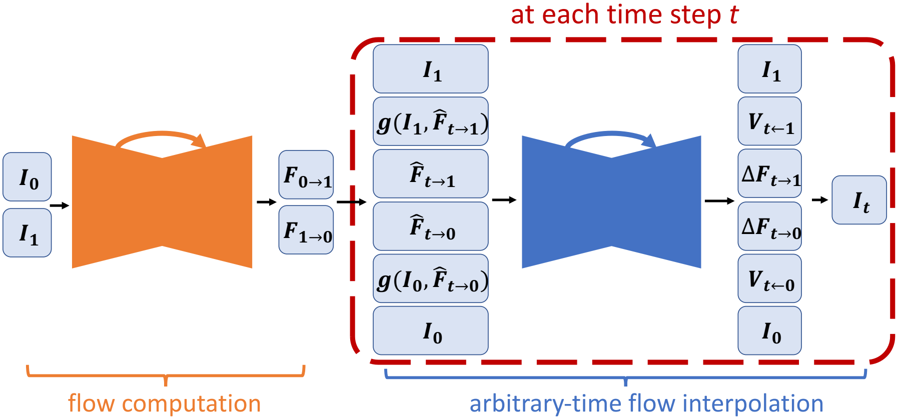
Goal: Tracking a moving object over a sequence of images. Optical flow is used to ensure the same object is tracked through multiple images.



Application II: Video Frame Interpolation [Jiang et al., 2018]

Link: `https://www.youtube.com/watch?v=MjViy6kyiqs`

Super SloMo



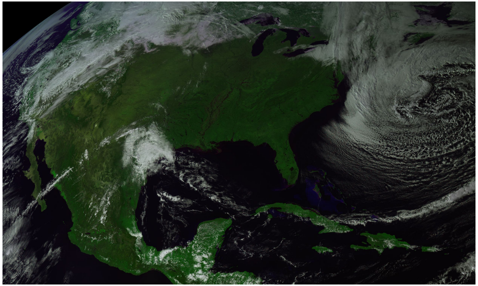
[Jiang et al., 2018]

Temporal Interpolation of Satellite Imagery

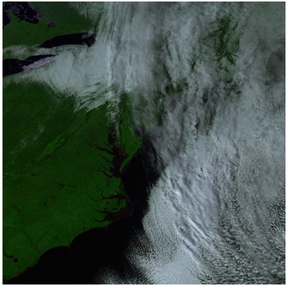
Spatial and Temporal Resolutions of GOES-16

Full Disk

Continental United States (CONUS)



Mesoscale



Spatial - 500 meters (visible), 1 km (near infrared), 2km (infrared)

Temporal - 10/15 min full disk, 5 minute CONUS, 30-60 second mesoscale

Temporal Interpolation of GOES-16

Mesoscale

- Flex mode allows the satellite to capture a user defined region to monitor major weather and environmental events.
- Coverage of 1000km by 1000km every 30 seconds (or two boxes every 1 minute).

Problem: Can we generate 1 minute full-disk coverage using machine learning and optical flow?

Approach: Apply the Super SloMo optical methodology by learning optical flows from mesoscale to interpolate between sequences of images.

Intermediate Frame Interpolation

Let $I_0, I_1, I_t \in \mathcal{R}^{H\times W\times C}$ such that $t \in (0, 1)$.
Construct an intermediate frame $\hat{I}_t$ from I_0 and I_1:

$$\hat{I}_t = \alpha \cdot g(I_0, F_{0\leftarrow t}) + (1-\alpha) \cdot g(I_1, F_{1\leftarrow t}) \tag{2}$$

$F_{0\leftarrow t}$ = Flow from I_t to I_0
$F_{1\leftarrow t}$ = Flow from I_t to I_1
g = backward warping function

Occlusion

Occlusion reasoning can be used to estimate the states of atmospheric variables over a static land surface by applying visbility maps, $V_{t\to 0}$ and $V_{t\to 1}$.

ie. For a given intermediate frame and pixel, is there cloud cover?

$$\hat{I}_t = \frac{1}{Z} \cdot \left((1-t) \cdot V_{t\to 0} \cdot g(I_0, F_{0\leftarrow t}) + t \cdot V_{t\to 1} \cdot g(I_1, F_{1\leftarrow t})\right) \quad (3)$$

where $Z = (1-t) \cdot V_{t\to 0} + t \cdot V_{t\to 1}$ is a normalization factor.

Deep neural networks are currently the state of the art for estimating $V_{t\to 0}, V_{t\to 1}, F_{0\leftarrow t}$, and $F_{0\leftarrow t}$.

Model Setup

Flow Network:

$$\hat{F}_{0\leftarrow 1}, \hat{F}_{1\leftarrow 0} = H_{\text{flow}}(I_0, I_1). \tag{4}$$

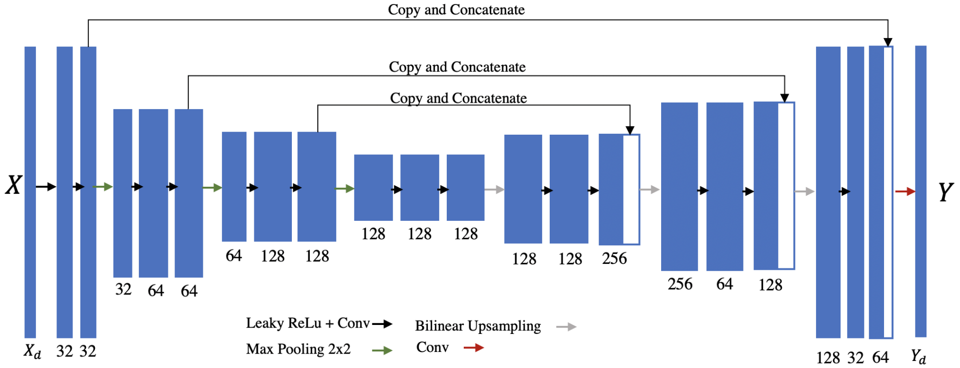
$$\begin{aligned} \hat{F}_{0\leftarrow t} &= -(1-t)tF_{0\leftarrow 1} + t^2 F_{1\leftarrow 0} \\ \hat{F}_{1\leftarrow t} &= (1-t)^2 F_{0\leftarrow 1} - t(1-t)F_{1\leftarrow 0} \end{aligned} \tag{5}$$

Interpolation Network:

$$V_{t\to 0}, V_{t\to 1}, \Delta\hat{F}_{0\leftarrow t}, \Delta\hat{F}_{1\leftarrow t} = H_{\text{Interp}}(I_0, I_1, \hat{F}_{0\leftarrow t}, \hat{F}_{1\leftarrow t}, g_0, g_1). \tag{6}$$

$$\begin{aligned} F_{0\leftarrow t} &= \hat{F}_{0\leftarrow t} + \Delta\hat{F}_{0\leftarrow t} \\ F_{1\leftarrow t} &= \hat{F}_{1\leftarrow t} + \Delta\hat{F}_{1\leftarrow t} \end{aligned} \tag{7}$$

Neural Network Architecture - UNet



Learning

Overall loss consists of a combination of reconstruction error, warping error, and smoothness regularization:

$$l = \lambda_r l_r + \lambda_w l_w + \lambda_s l_s. \tag{8}$$

Reconstruction loss is the euclidean distance between observed and predicted intermediate frames:

$$l_r = \frac{1}{N} \sum_{i=1}^{N} ||\hat{I}_{t_i} - I_{t_i}||_2. \tag{9}$$

Warping loss is used to optimize estimated optical flows between input and intermediate frames:

$$\begin{aligned} l_w = {} & ||I_0 - g(I_1, F_{0\to1})|| + ||I_1 - g(I_0, F_{1\to0})|| \\ & + \frac{1}{N} \sum_{i=1}^{N} ||I_{t_i} - g(I_0, F_{0\to t_i})||_2 + \frac{1}{N} \sum_{i=1}^{N} ||I_{t_i} - g(I_1, F_{1\to t_i})||_2 \end{aligned} \tag{10}$$

Smoothness loss ensures locally smooth flows:

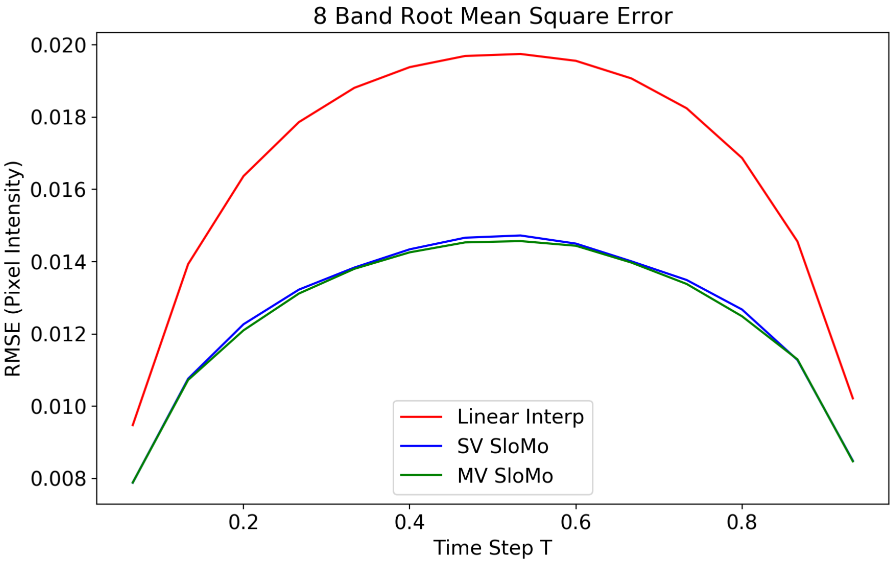
$$l_s = ||\Delta F_{0\to1}||_1 + ||\Delta F_{1\to0}||_1 \tag{11}$$

Results I

Table: Root mean square error (RMSE) over a held out test set of every 5 days in 2019 mesoscale data for a 15 minute temporal enhancement.

index	Linear	SV-SloMo	MV-SloMo	Linear	SV-SloMo	MV-SloMo
1	0.0232	**0.0172**	**0.0172**	0.0231	0.0171	**0.0170**
2	0.0329	**0.0260**	0.0261	0.0329	**0.0261**	**0.0261**
3	0.0288	**0.0218**	**0.0218**	0.0287	0.0217	**0.0216**
4	–	–	–	0.0095	0.0059	**0.0058**
5	–	–	–	0.0214	0.0168	**0.0167**
6	–	–	–	0.0137	0.0100	**0.0098**
7	–	–	–	0.0017	0.0012	**0.0011**
8	–	–	–	0.0026	0.0019	**0.0018**
3 Band Mean	0.0283	**0.0217**	**0.0217**	0.0282	**0.0216**	**0.0216**
8 Band Mean	–	–	–	0.0180	0.0136	**0.0135**

Results II


8 Band Root Mean Square Error
RMSE (Pixel Intensity)
0.020
0.018
0.016
0.014
0.012
0.010
0.008
0.2
0.4
0.6
0.8
Time Step T
Linear Interp
SV SloMo
MV SloMo

Video

Link: `https://www.youtube.com/watch?v=NeMXPQw3CJU`

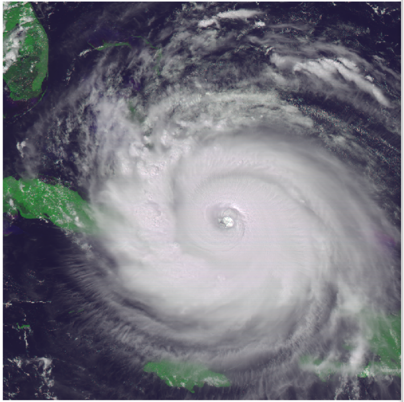
Extracting Pixel-wise Flow Vectors

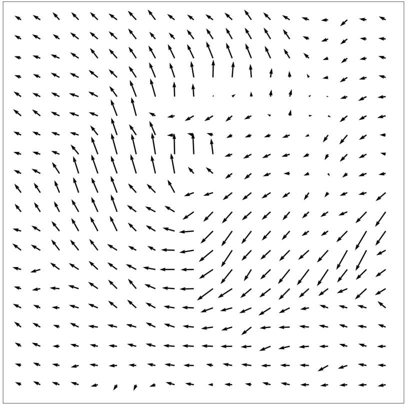
Flow Vectors

Flow vectors, $F_{0 \leftarrow t}$ and $F_{1 \leftarrow t}$, learned from the interpolation model has the following properties:

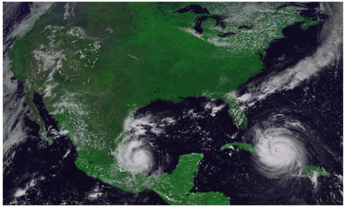
- Each F consists of u and v components representing horizontal and vertical velocities
- Direction is extracted from u and v
- Locally smooth vector magnitude and direction
- Each pixel is 2km, temporal period is 15 minutes $(u * 2/15 * 4 = km/hour)$

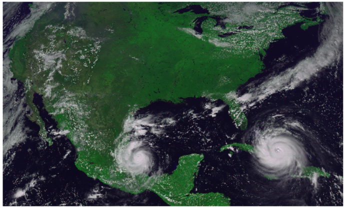
Mesoscale - Hurricane Irma - September 8 2017



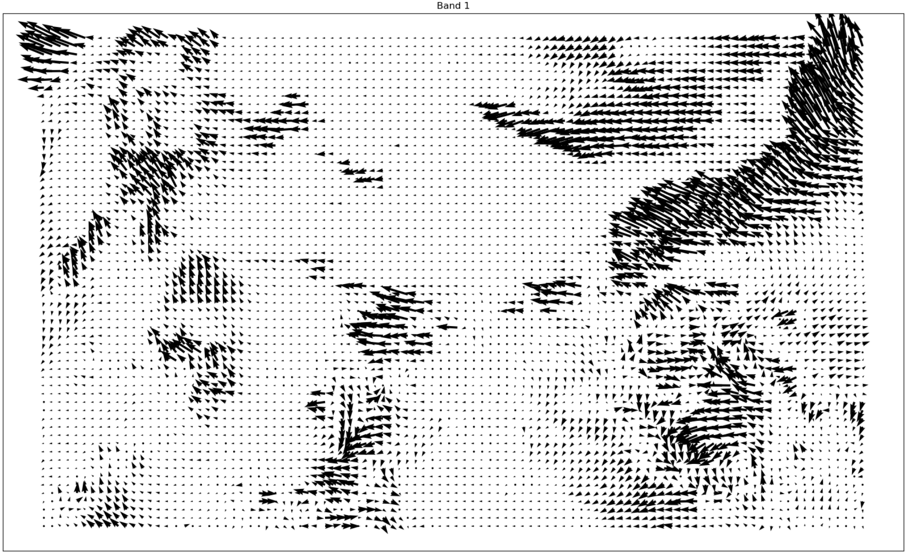


CONUS - September 8 2017

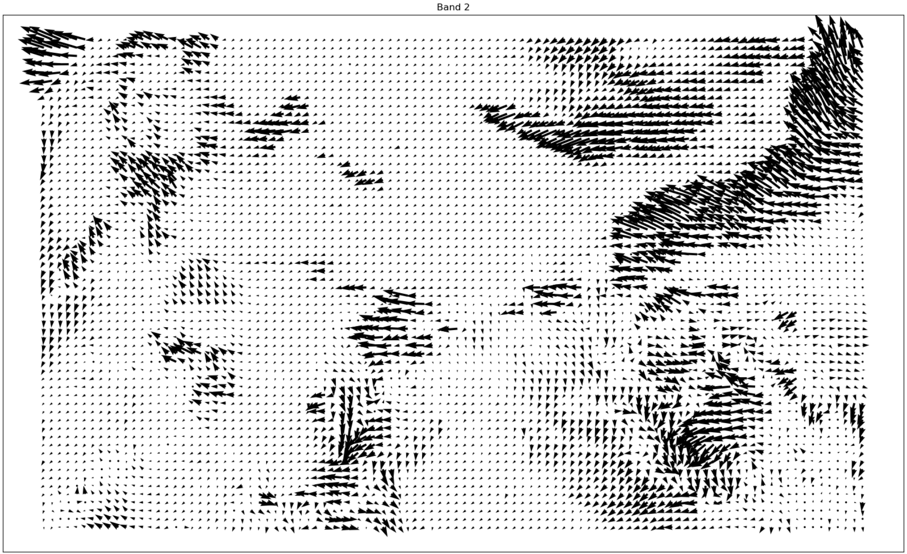




Band 1 - Visible - Blue

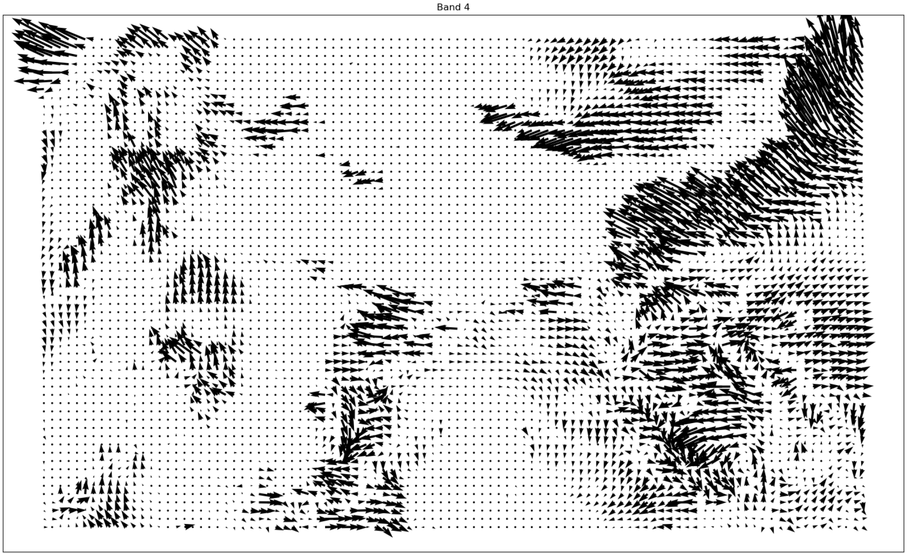


Band 2 - Visible - Red

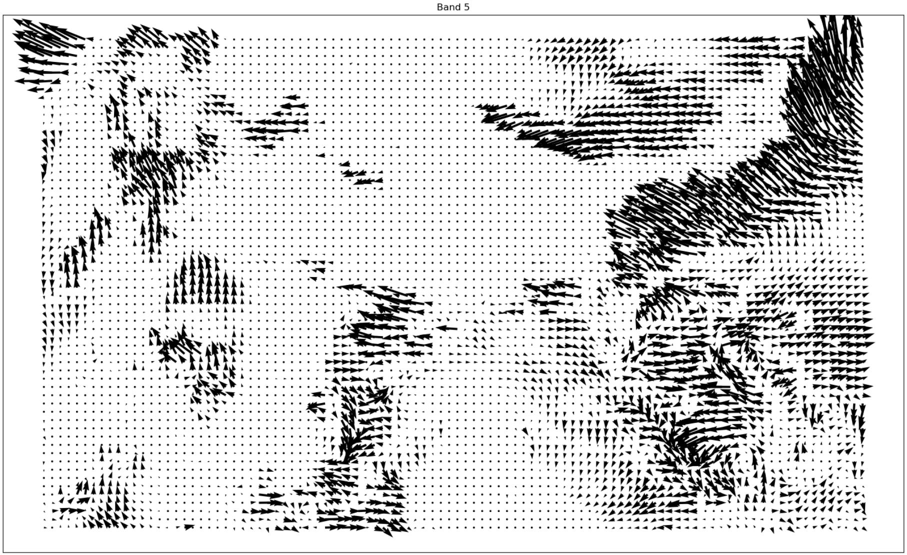


Band 3 - Near-IR

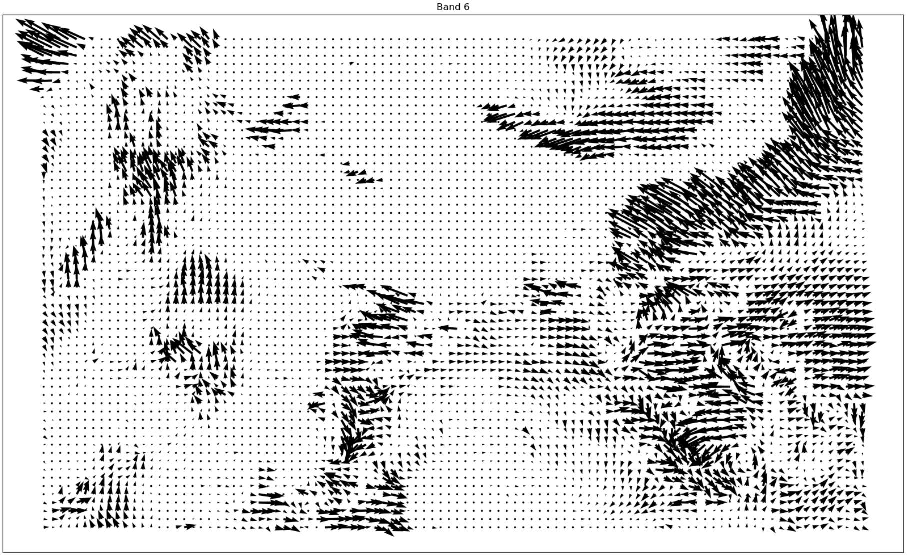
Band 4 - Near-IR



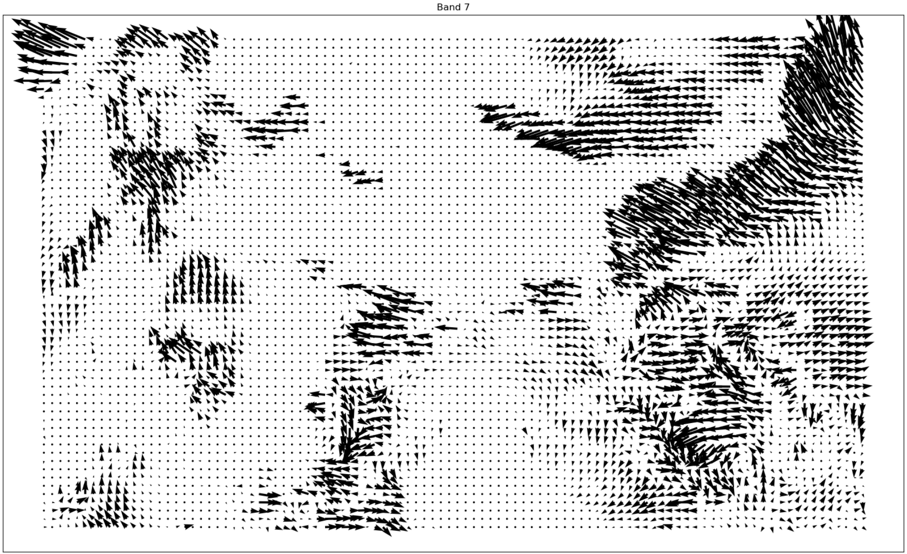
Band 5 - Near-IR



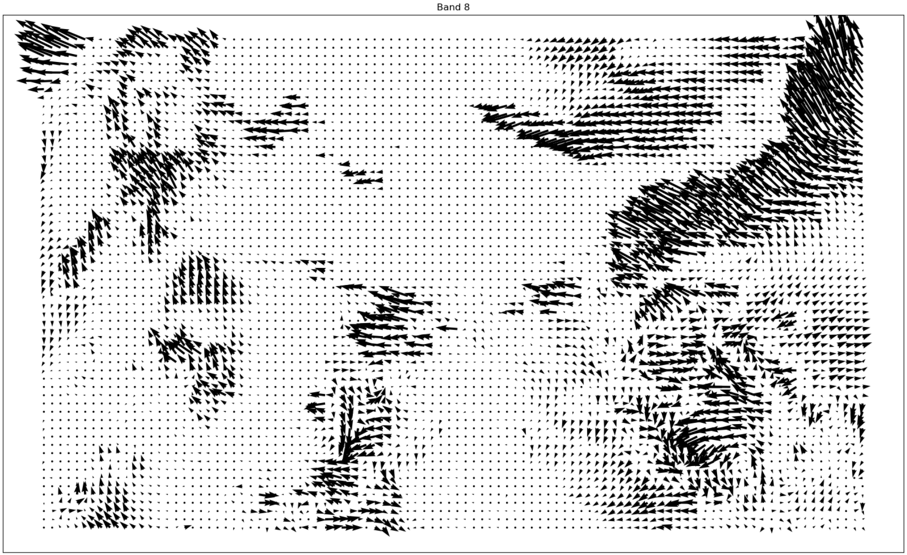
Band 6 - Near-IR



Band 7 - IR



Band 8 - Near-IR - Upper-Level Tropospheric Water Vapor



Conclusions

Conclusions

1. Key Points
   - Optical flows are numerically estimated with deep neural networks
   - Flow vectors are used to track the movement of objects in images, such as clouds
   - The intermediate frame interpolation approach can estimate flow vectors for any time in the domain
2. Next Steps
   - How are the flow vectors related to wind? What exactly is being captured?
   - Use ground truth data (Aeolus?) to understand the vectors
   - Simplify optical flow model
3. Optical flow applied to nowcasting of geostationary data is another promising direction.

References I

Bertinetto, L., Valmadre, J., Henriques, J. F., Vedaldi, A., and Torr, P. H. (2016).
Fully-convolutional siamese networks for object tracking.
In *European conference on computer vision*, pages 850–865. Springer.

Horn, B. K. and Schunck, B. G. (1981).
Determining optical flow.
Artificial intelligence, 17(1-3):185–203.

Jiang, H., Sun, D., Jampani, V., Yang, M.-H., Learned-Miller, E., and Kautz, J. (2018).
Super slomo: High quality estimation of multiple intermediate frames for video interpolation.
In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 9000–9008.