

Data Assimilation for Irradiance Forecasting

Travis Harty¹, M. Morzfeld², W.F. Holmgren³, A.T. Lorenzo³

Program in Applied Mathematics¹
Mathematics Department²
Hydrology & Atmospheric Sciences³
University of Arizona

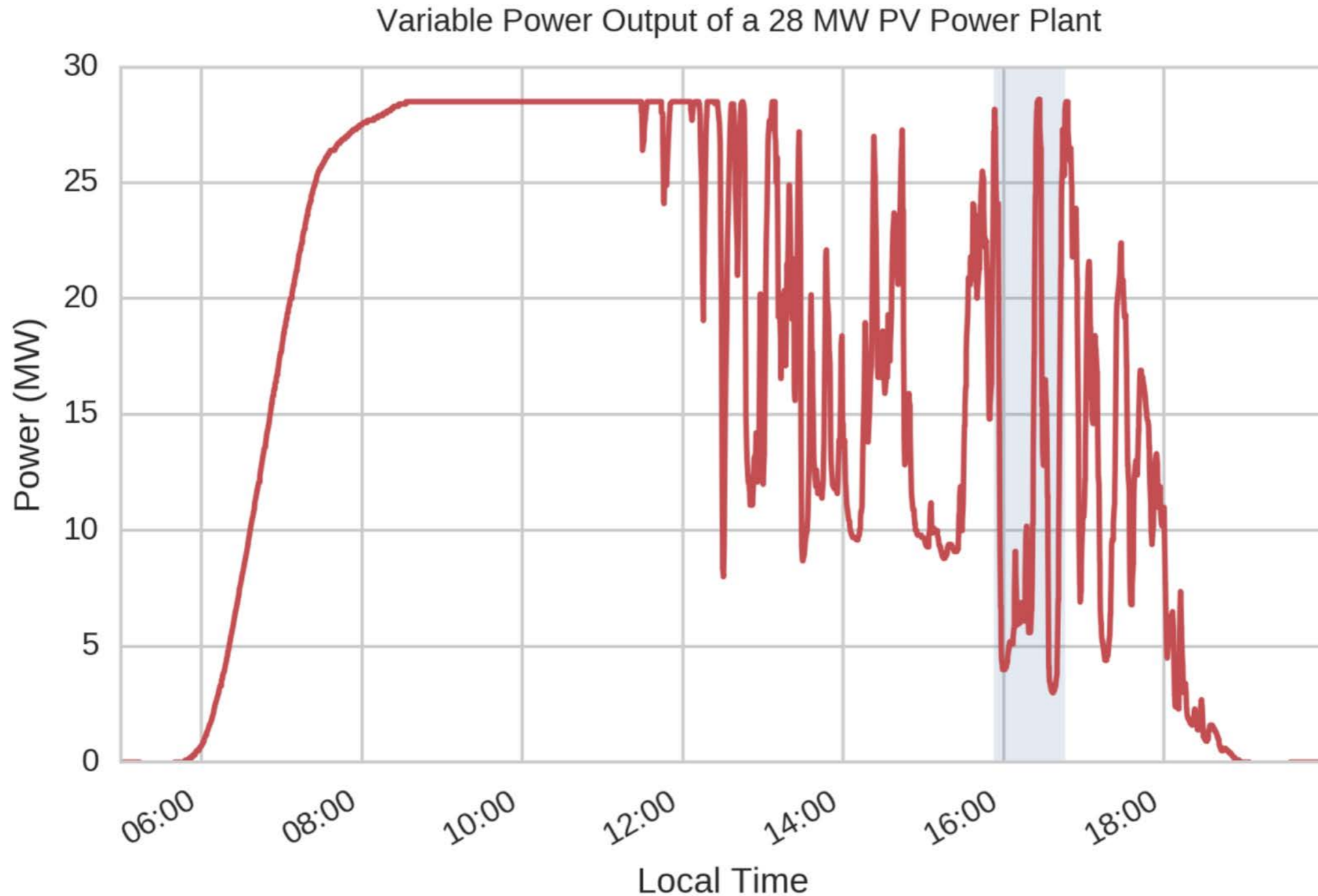


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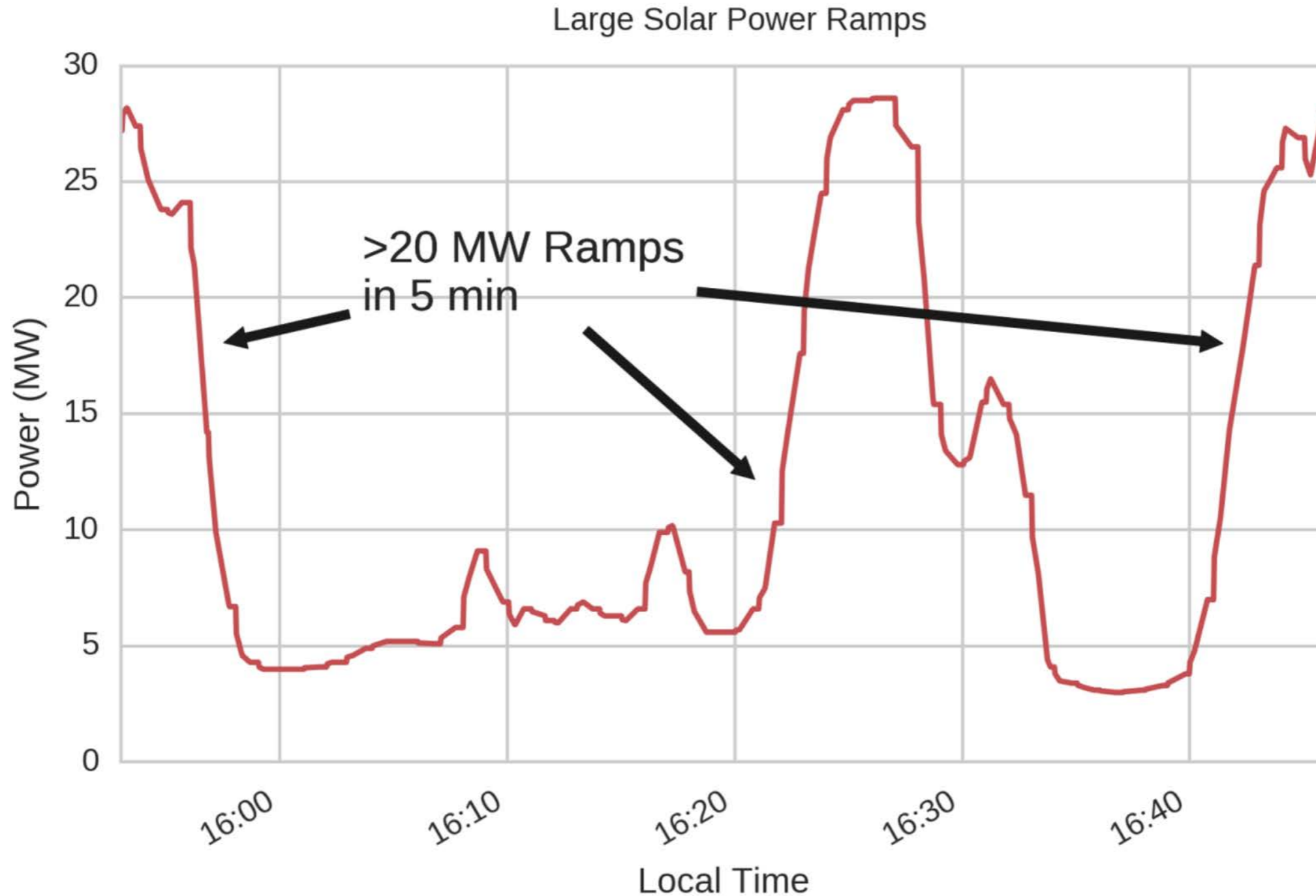


Irradiance forecasting



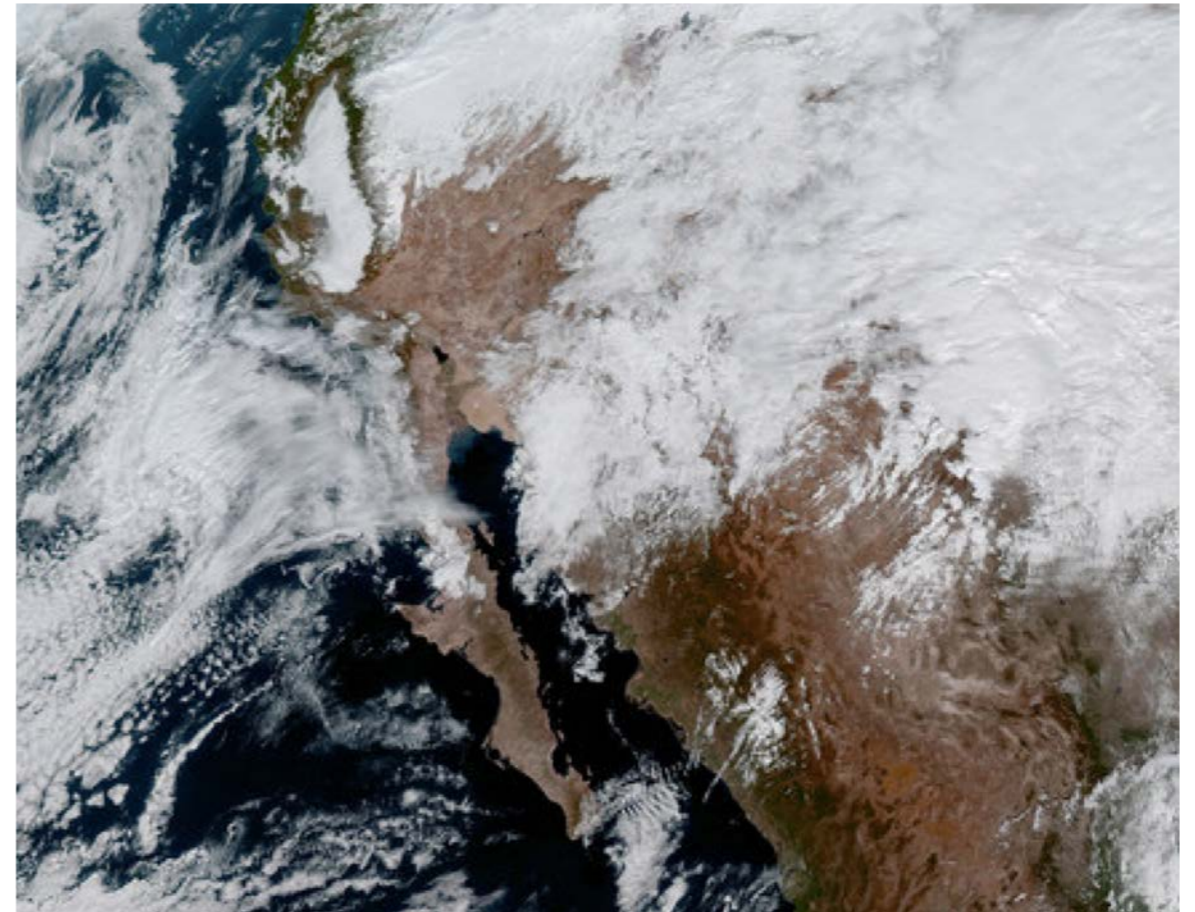
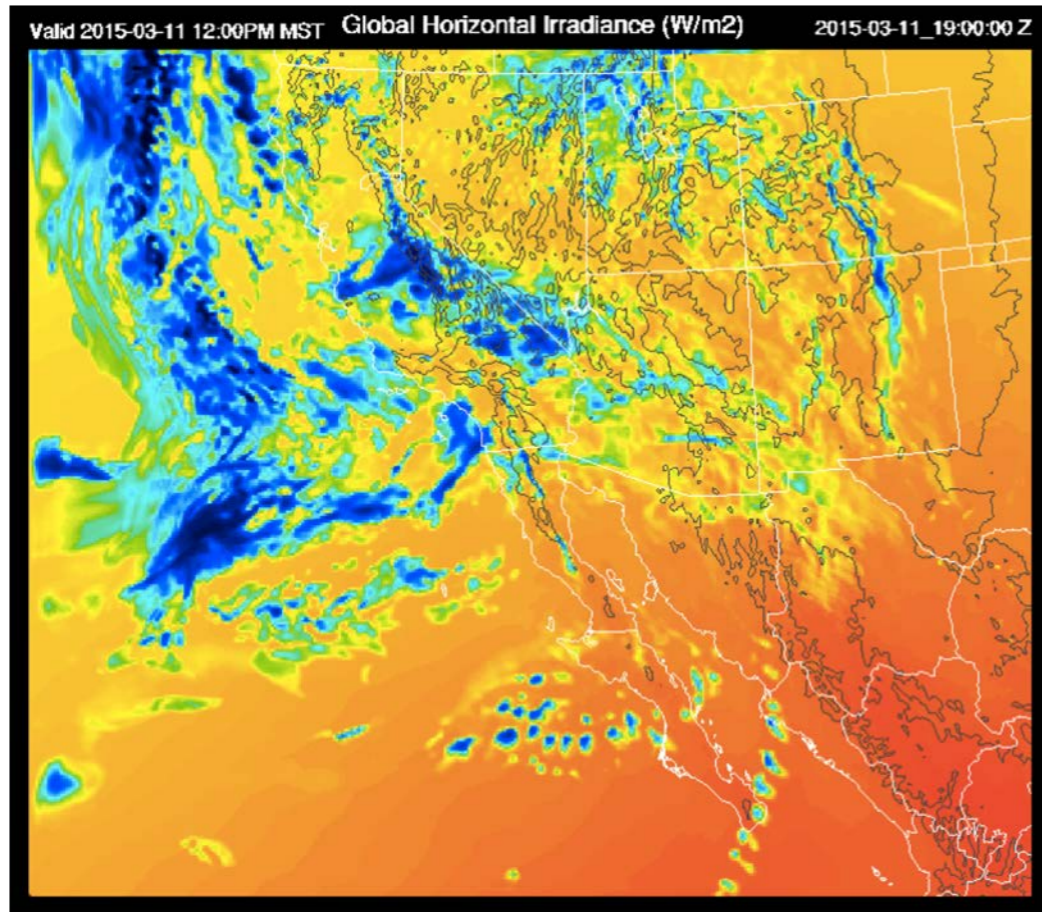
- Several 20 MW ramps taking about 5 minutes
- A 20 MW is about equivalent to the demand of 10,000 homes

Irradiance forecasting



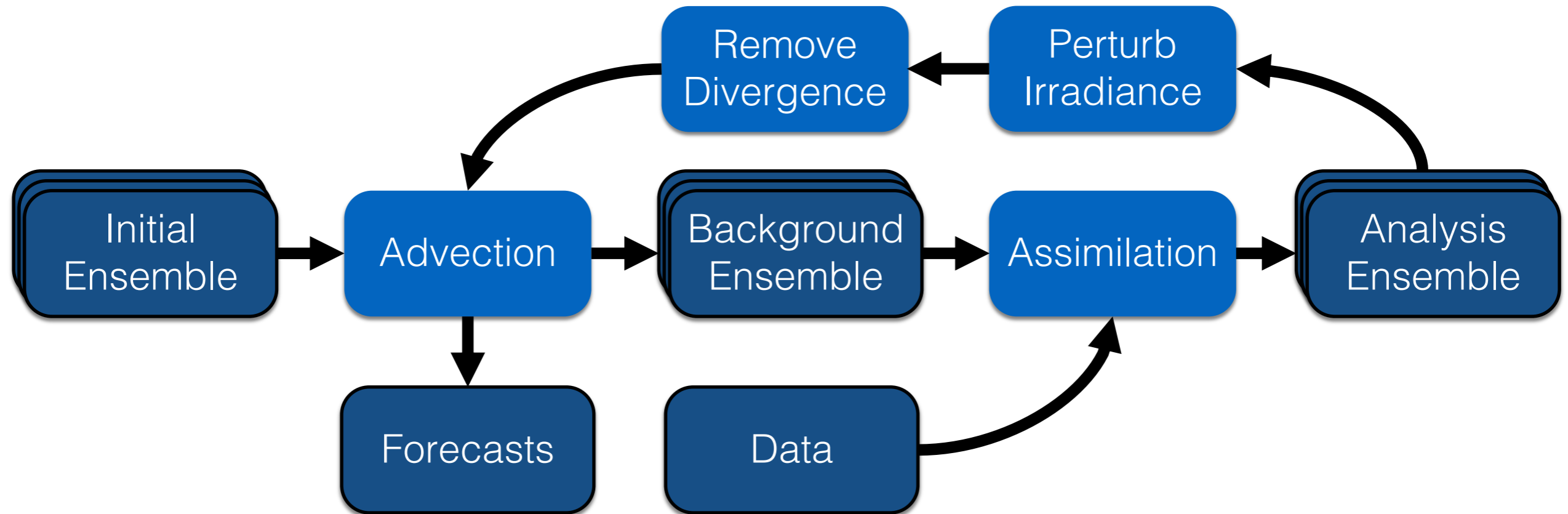
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Irradiance forecast techniques



- The University of Arizona Hydrology and Atmospheric Science WRF model forecasts irradiance.
- Can we do better using more data on intra-hour timescales?
- Require irradiance fields on the scale of a city (Tucson, AZ) every 5 minutes
- We will advect a 2D cloud field using a 2D cloud motion field.
- This work will focus on improving the cloud motion field.

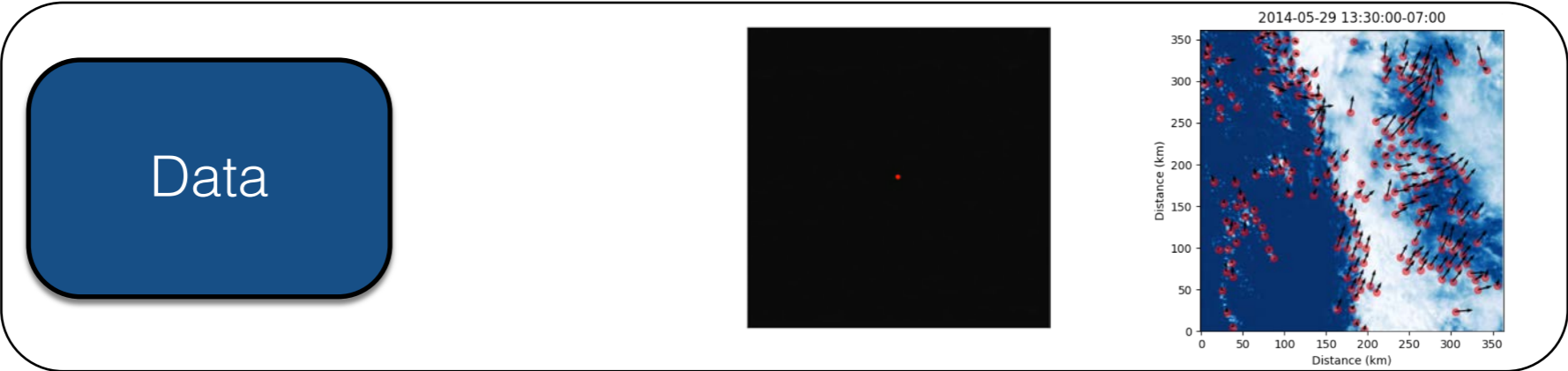
Forecast system



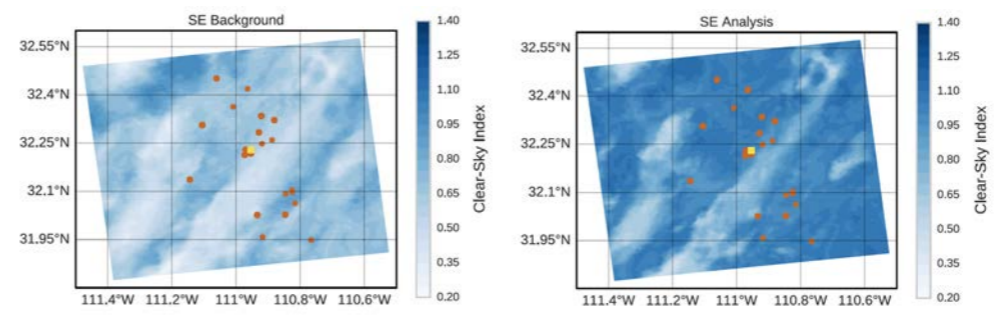
- Each ensemble member has unique cloud field and cloud motion field
- The LETKF and EnKF are used for assimilation
- Irradiance perturbation and divergence removal will be discussed later

(eg. Hunt et al., 2007)(eg. Burges et al., 1998)

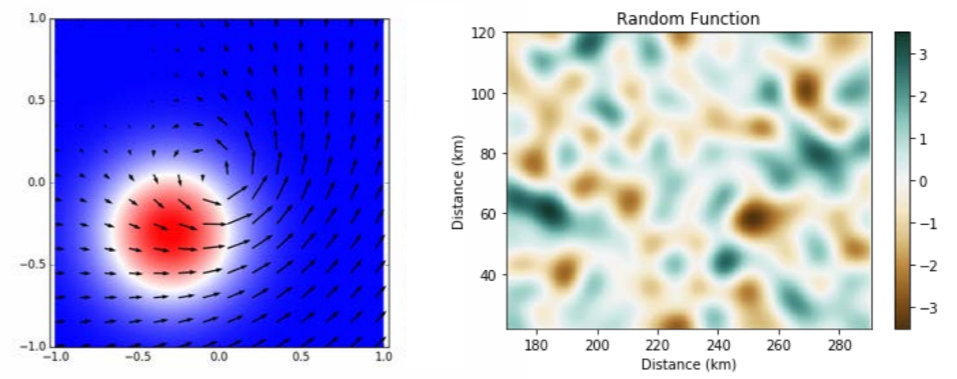
Overview



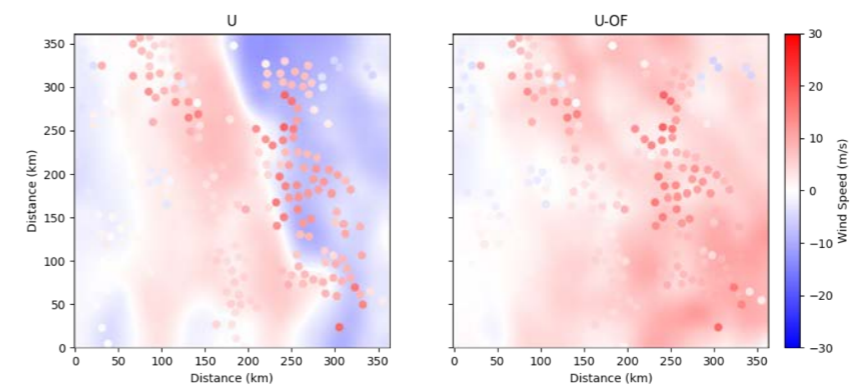
Previous Work



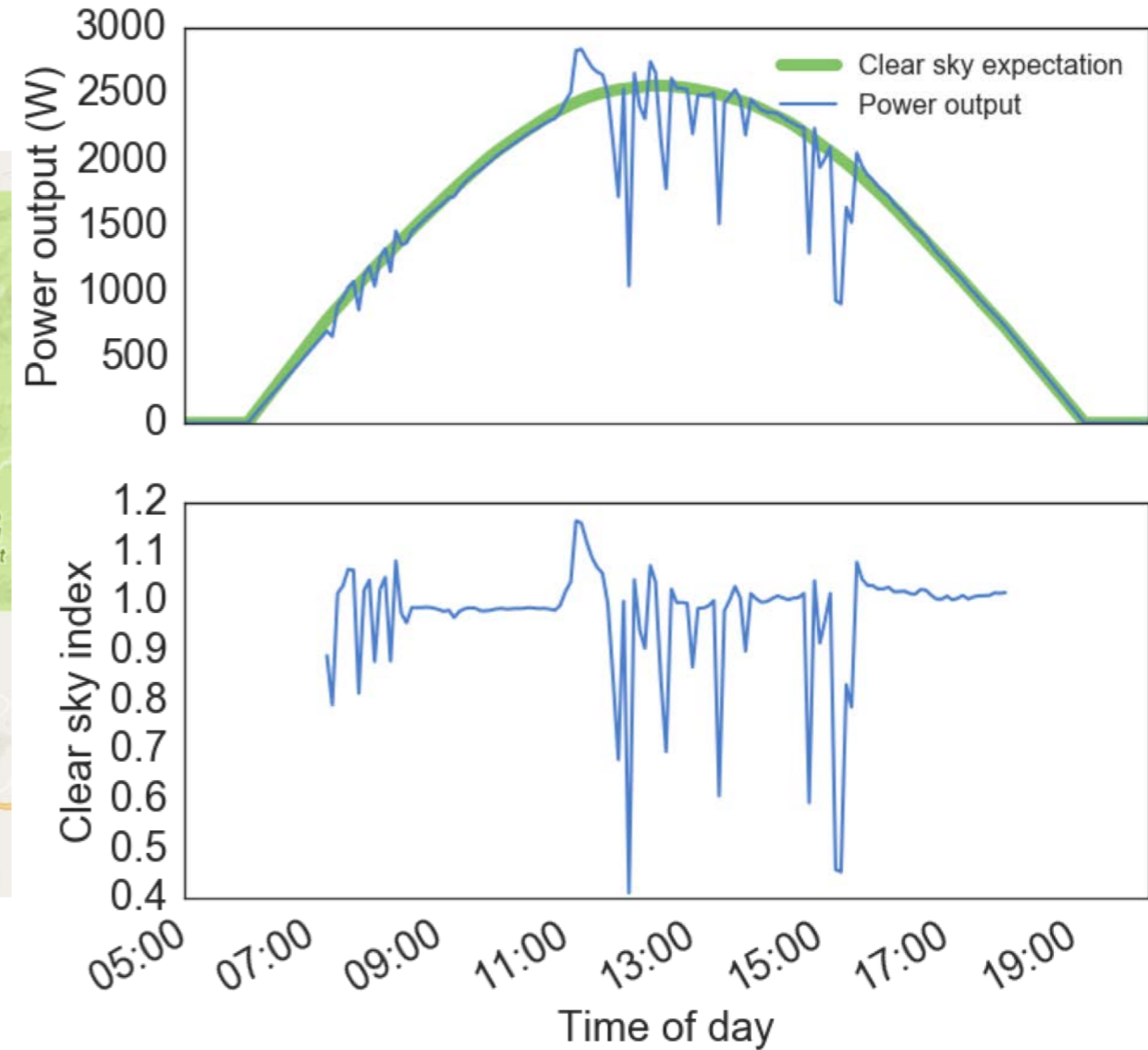
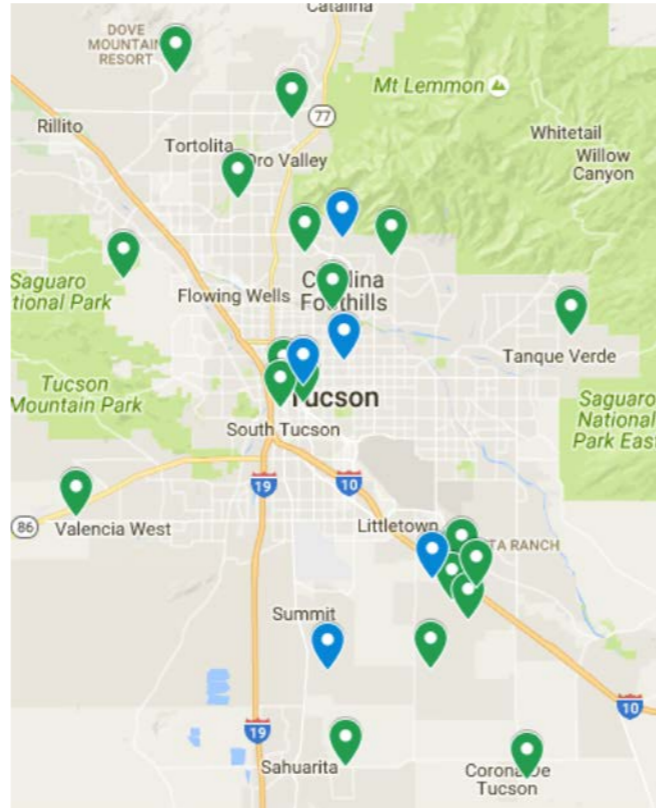
Model & Perturbation



Assimilation



Sensor data



- 15 Solar arrays
- 12 irradiance sensors
- Data is collected approximately every 5 minutes

- Normalized by clear sky expectation
- Unitless and detrended

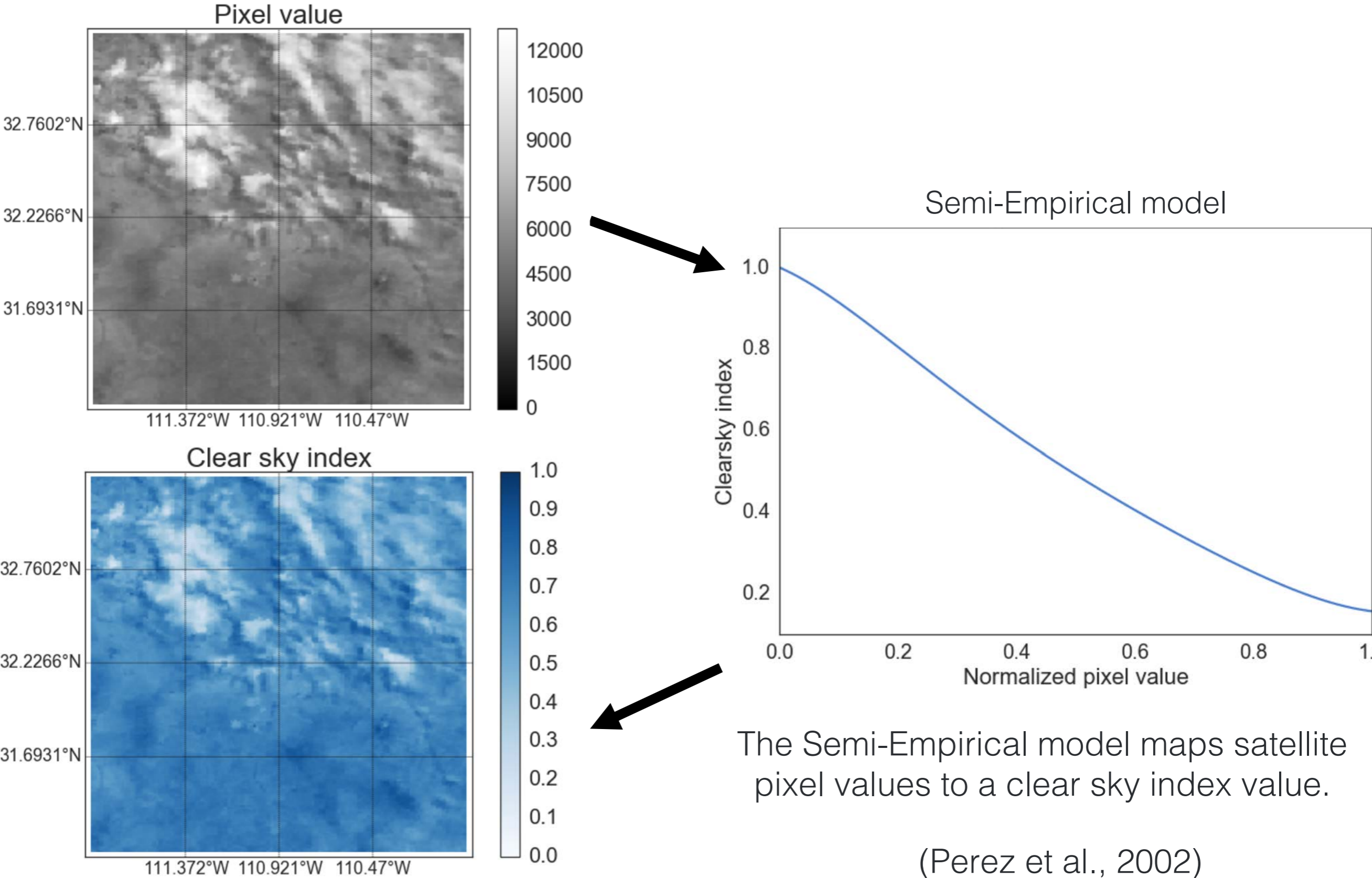
Satellite images

time: 2014-04-15 06:00:00-07:00

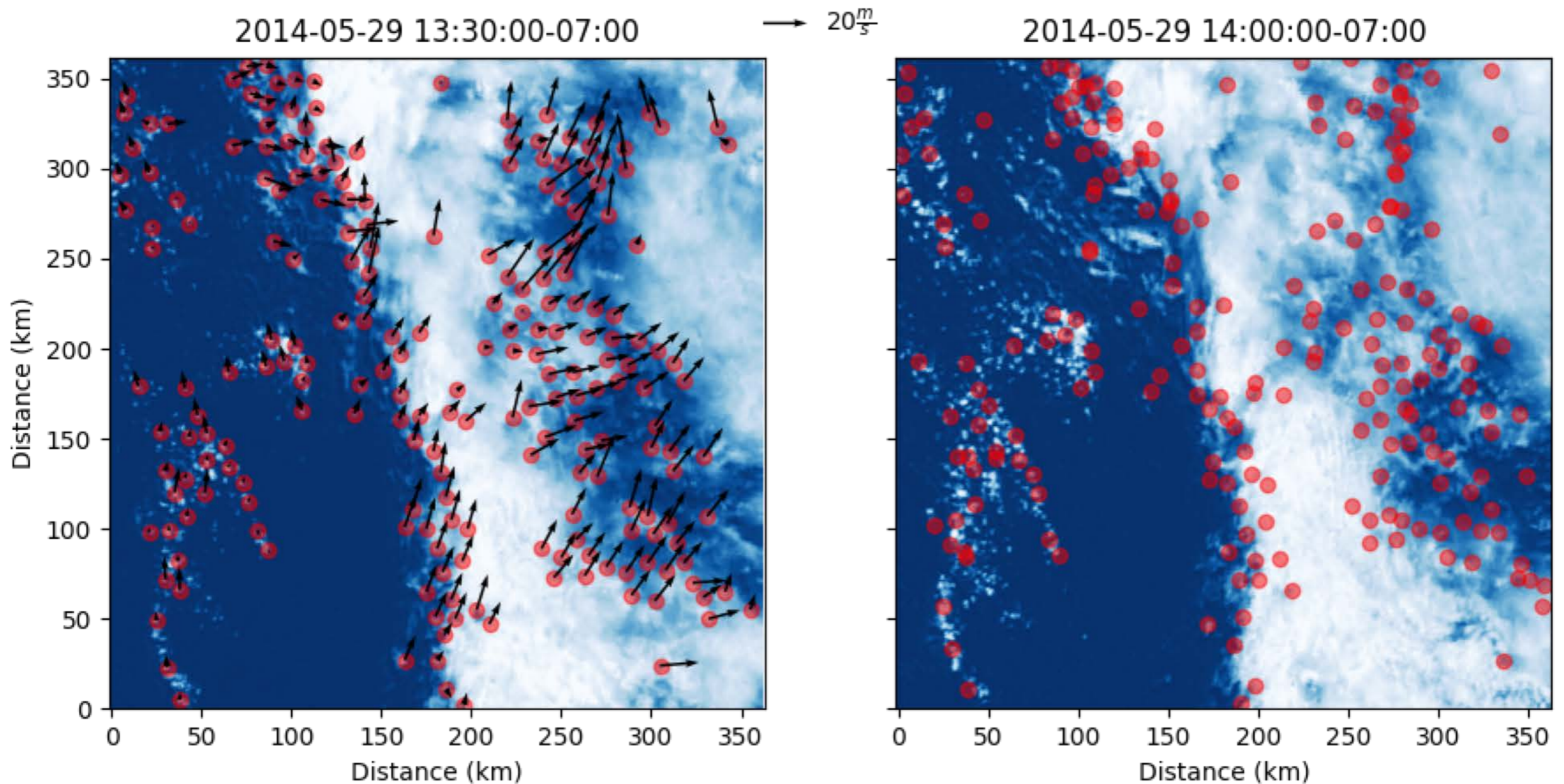


- Geostationary satellite images (GOES-15)
- Available every 15 minutes
- Spatial resolution of 1 km²
- Converted to clear sky index (normalized irradiance)

Satellite data

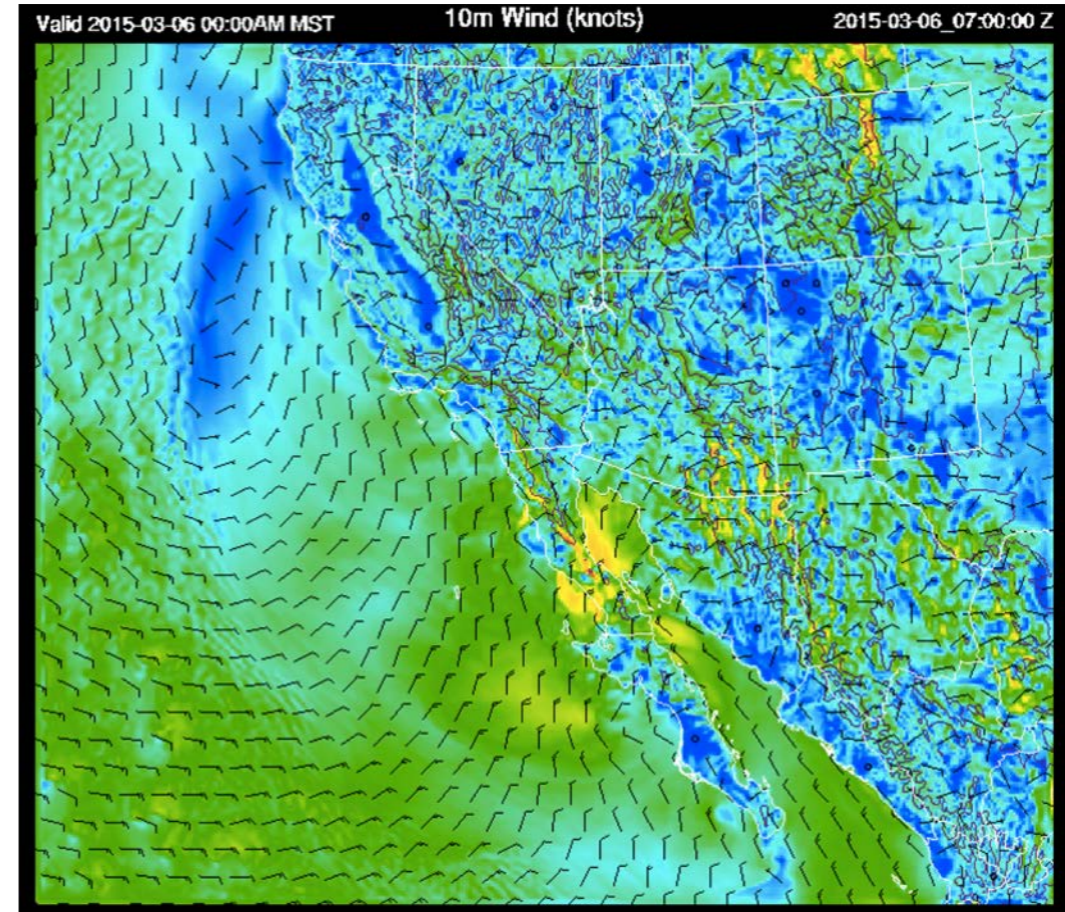
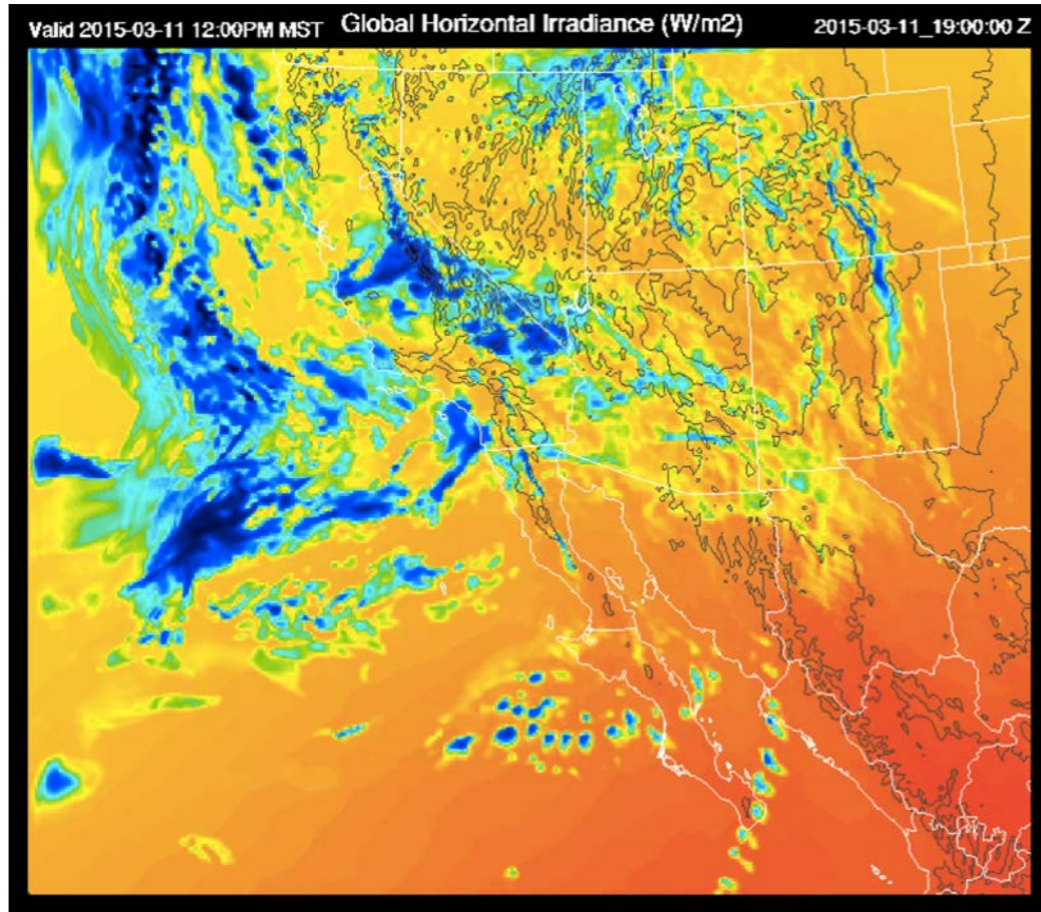


Optical flow



- Choose features on the satellite image based on the gradient of the image and the image's windowed variance
- Track features to estimate the cloud motion field

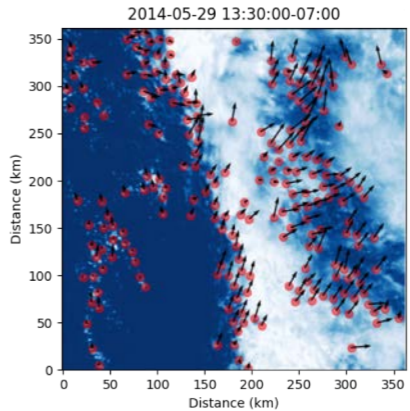
Numerical Weather Prediction (NWP)



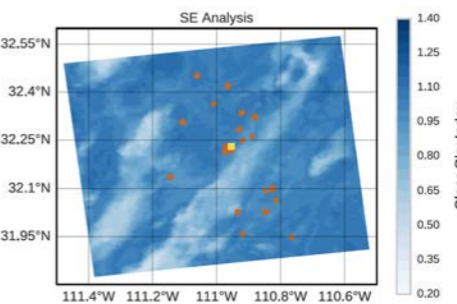
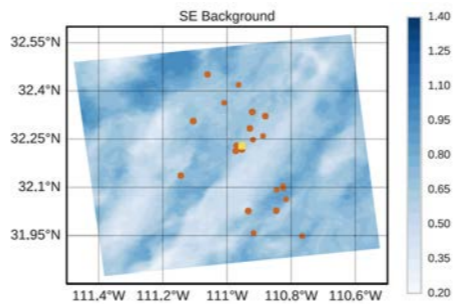
- It has an inner domain with a horizontal resolution of 1.8 km which covers Arizona and New Mexico
- We will use U and V wind components from vertical level with highest relative humidity

Overview

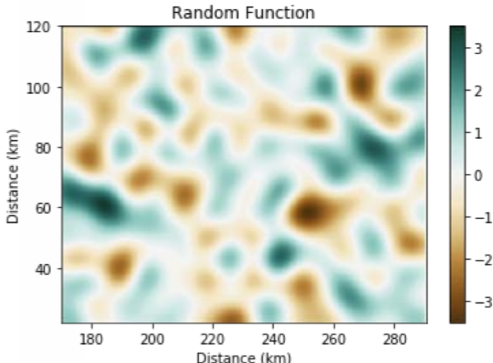
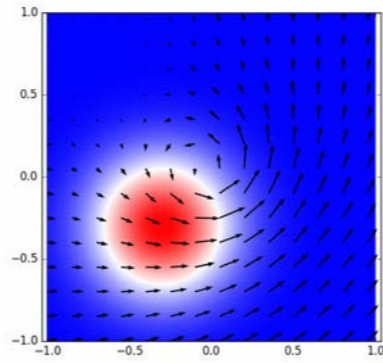
Data



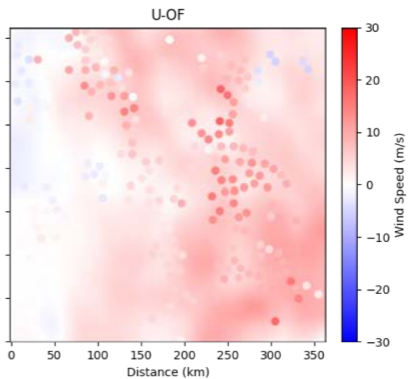
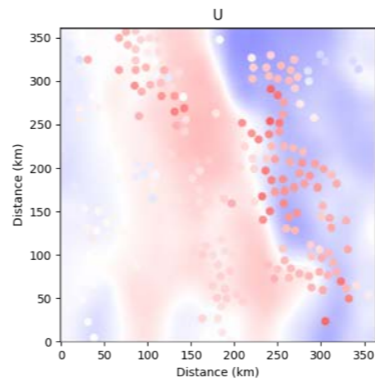
Previous Work



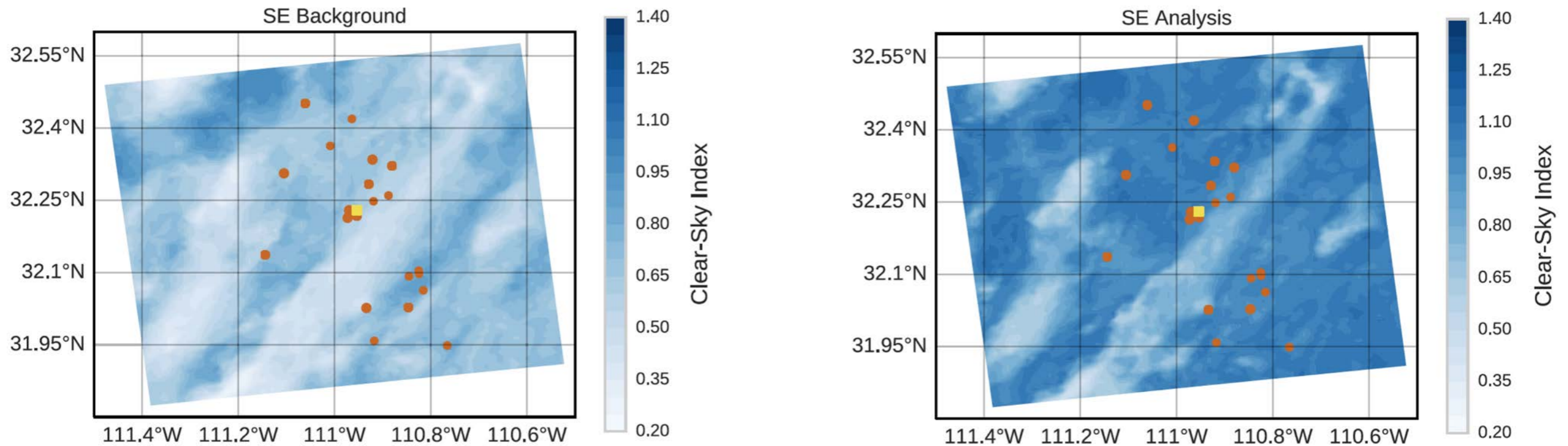
Model & Perturbation



Assimilation



Optimal interpolation of ground sensors

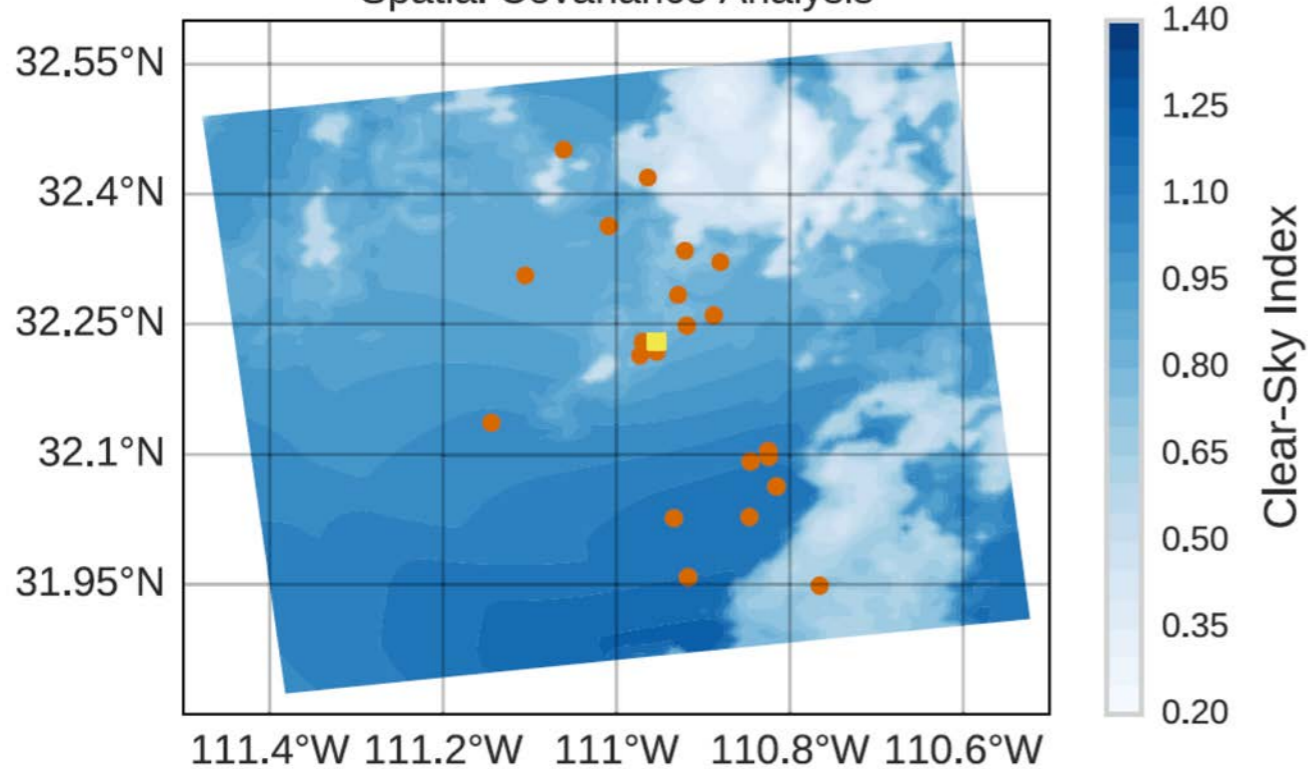


$$\mathbf{P} = \mathbf{D}^{1/2} \mathbf{C} \mathbf{D}^{1/2}$$
$$\mathbf{W} = \mathbf{P} \mathbf{H}^T (\mathbf{R} + \mathbf{H} \mathbf{P} \mathbf{H}^T)^{-1}$$
$$\mathbf{x}^a = \mathbf{x}^b + \mathbf{W} (\mathbf{y} - \mathbf{H} \mathbf{x}^b)$$

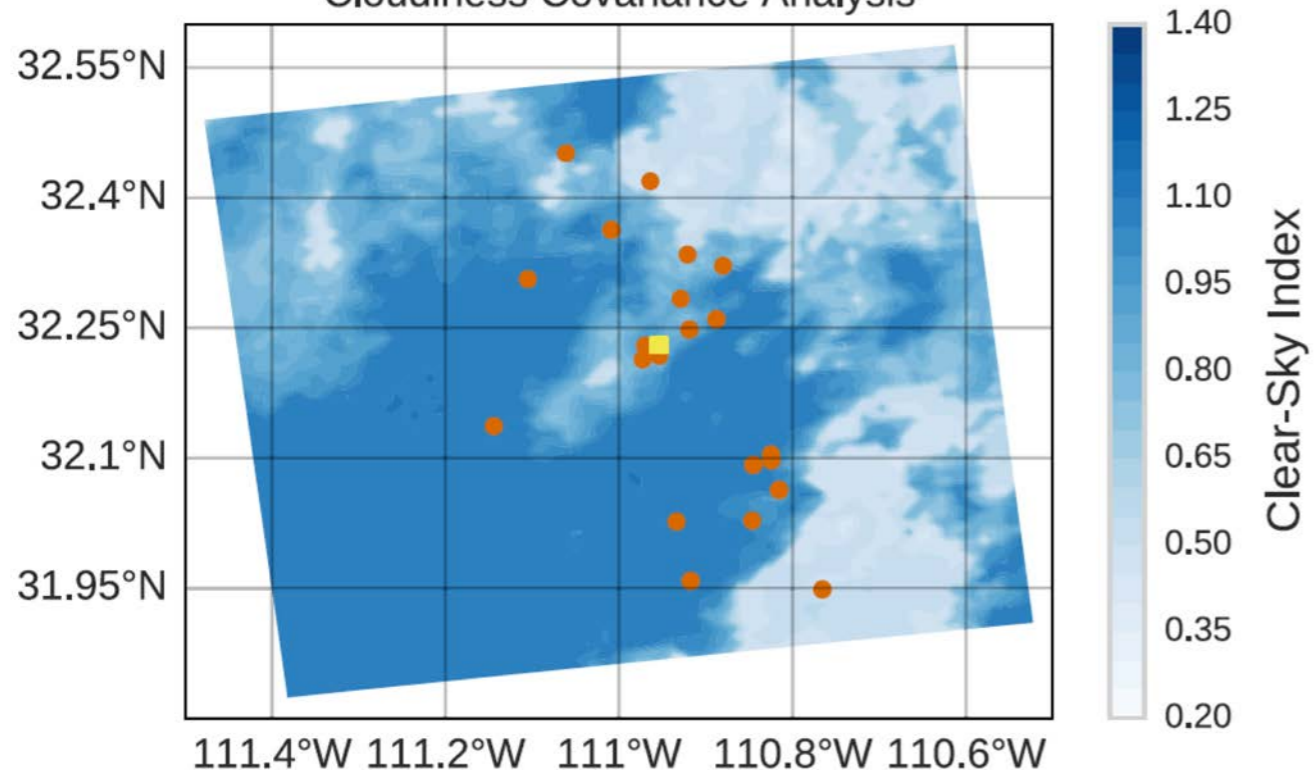
- Ground data is sparse but accurate.
- Satellite derived CSI fields are available on a large scale, but less accurate.
- Take semi-empirical (SE) model as background and assimilate ground sensors using optimal interpolation

Different choices of C

Spatial Covariance Analysis



Cloudiness Covariance Analysis



$$r_{i,j} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$$

- Correlation based on spatial distance between locations
- Produces gradient which is not seen in original satellite image

Correlation Matrix

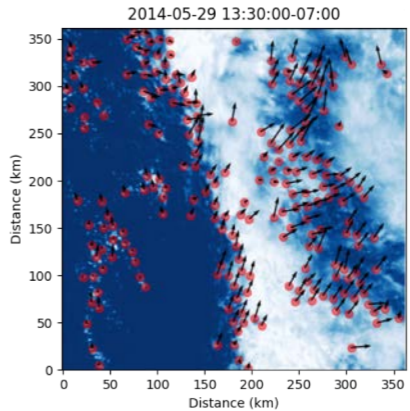
$$\mathbf{C}_{i,j} = \exp\left(-\frac{r_{i,j}^2}{2l^2}\right)$$

$$r_{i,j} = |z_i - z_j|$$

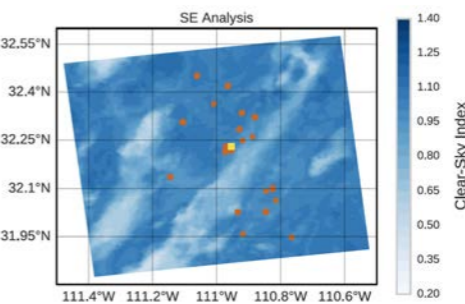
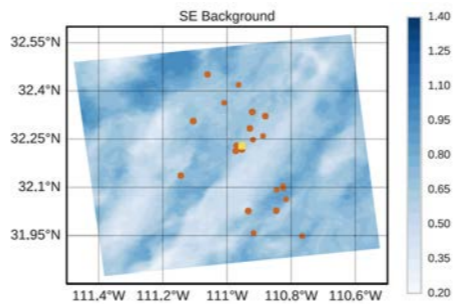
- Distance based difference in normalized satellite value, z .
- Produces analysis which is more physically meaningful

Overview

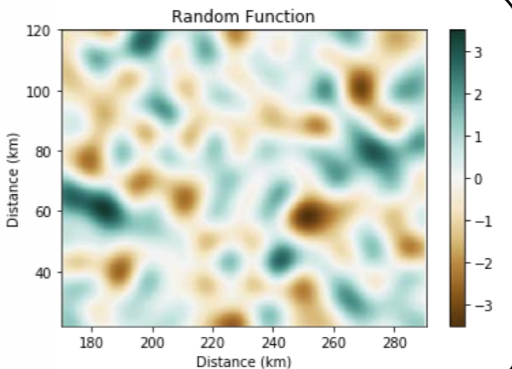
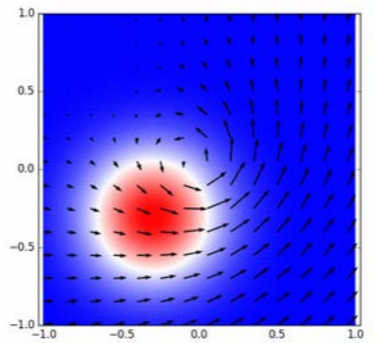
Data



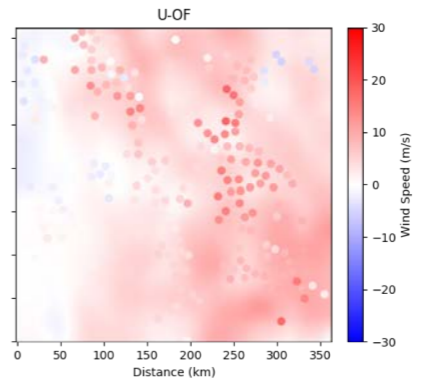
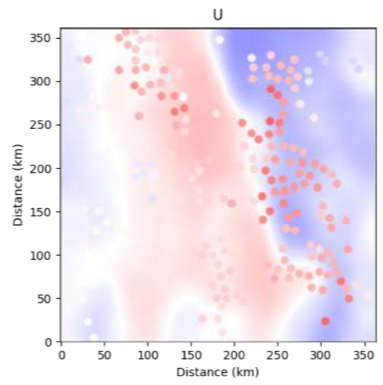
Previous Work



Model & Perturbation



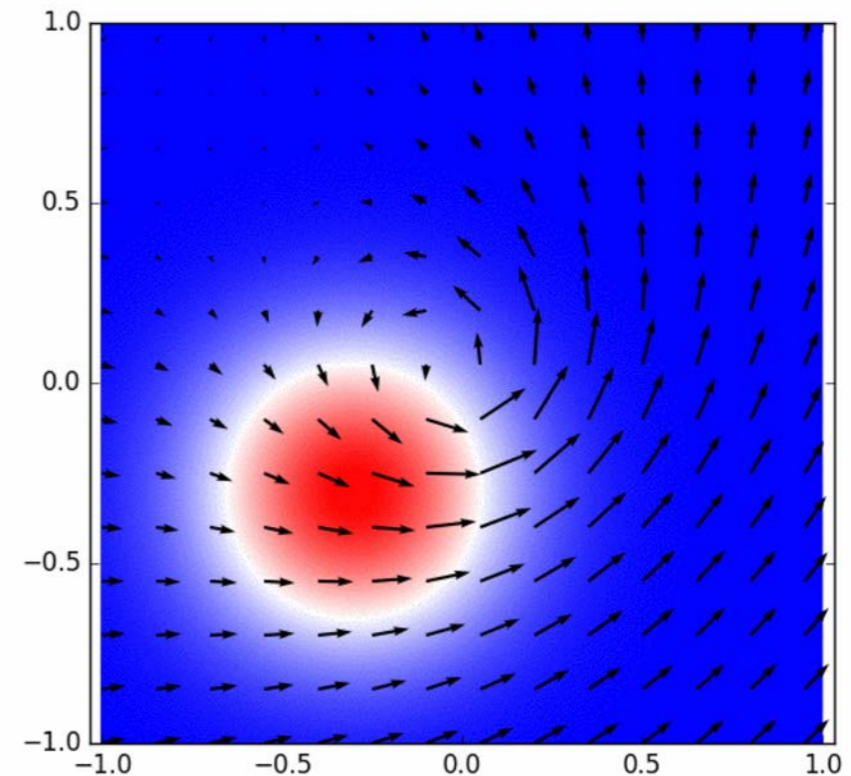
Assimilation



Advection model

A Typical weather model must track many things:

- Wind in three directions
- Density
- Pressure
- Temperature
- Moisture

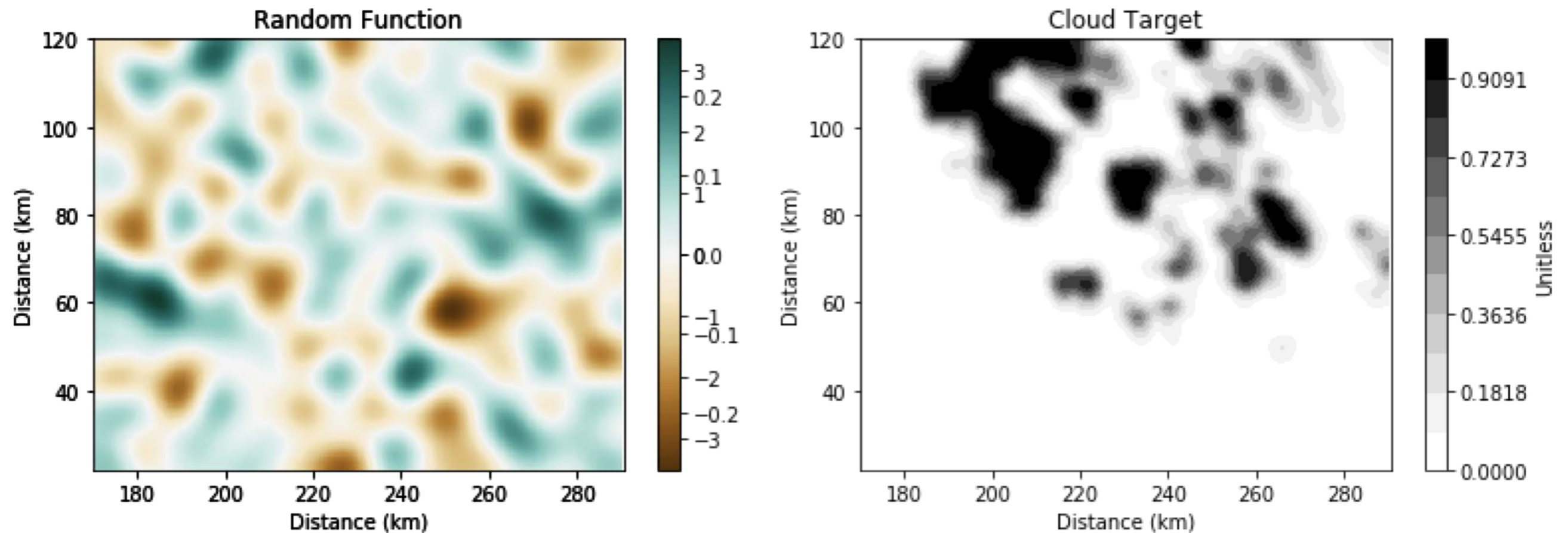


Simplification is needed to run operational forecasts. Previous studies have shown that satellite advection out performs NWP for short term (3-6 hour) forecasts.

- Track only 2D wind at cloud layer
- Advect clouds represented as normalized pixel value
- Update wind fields hourly based on a numerical weather model
- Use 3rd order R-K method in time and 4th order special derivative based on WRF advection scheme

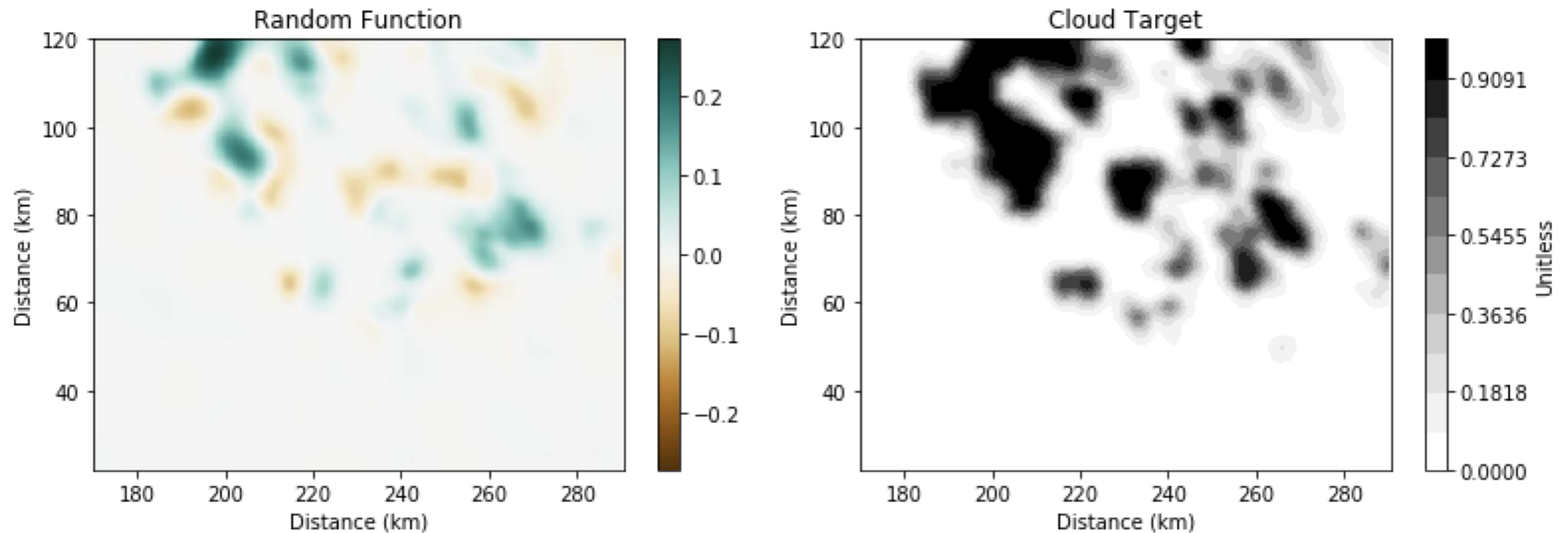
(Kalnay, 2002)(Perez et al., 2010)

Normalized irradiance perturbation



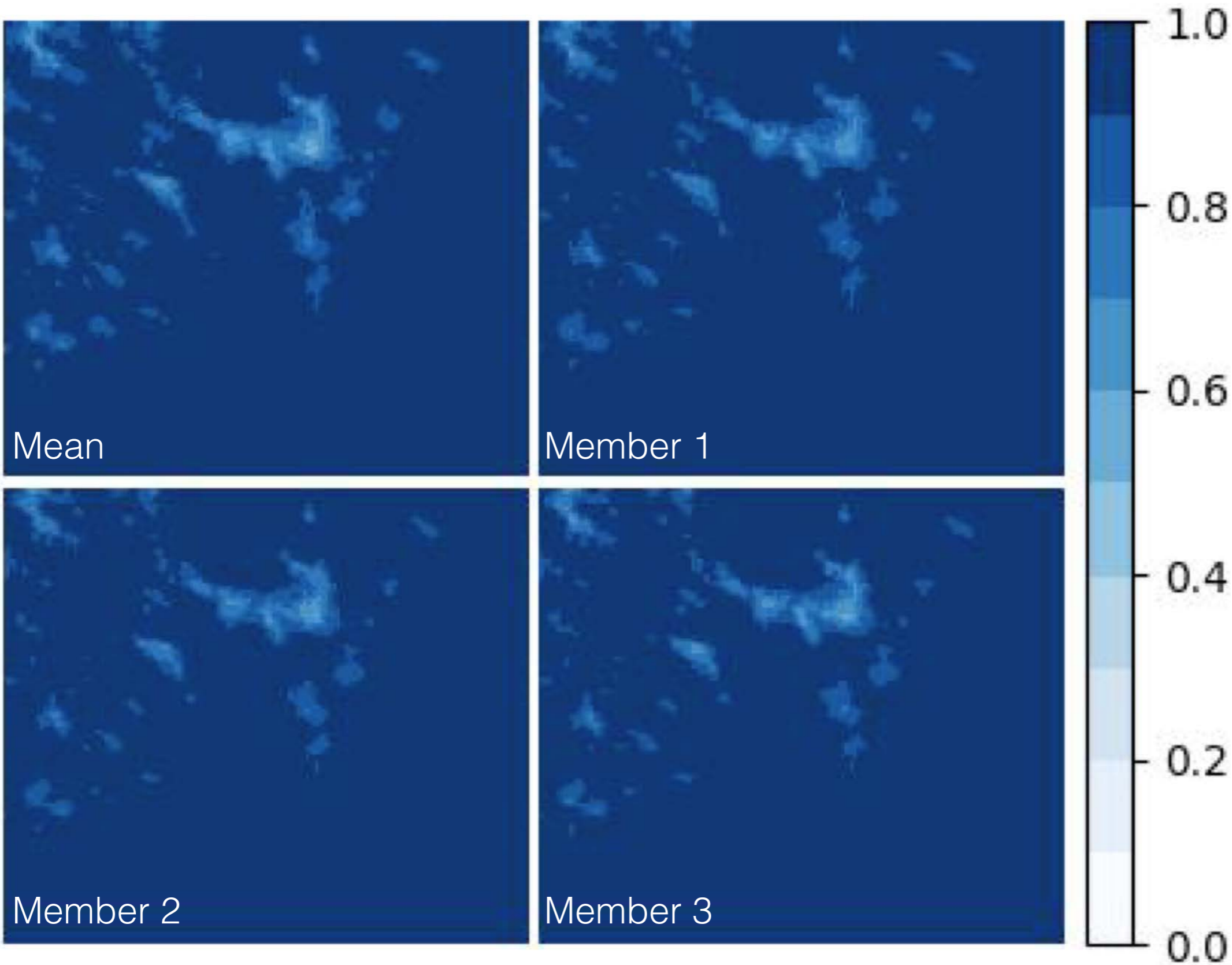
- Create random function with desired random properties
- Target only those parts of the image which you wish to perturb
- In our case, we target cloudy areas to capture changes taking place inside and on the edges of clouds

Normalized irradiance perturbation



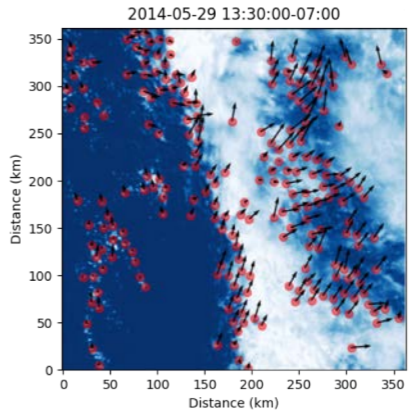
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Ensemble of perturbed fields

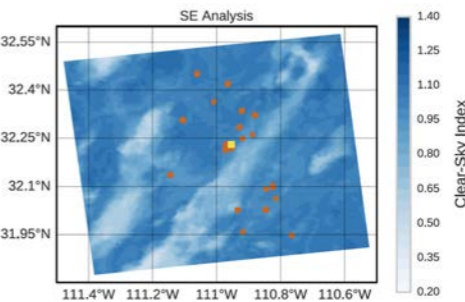
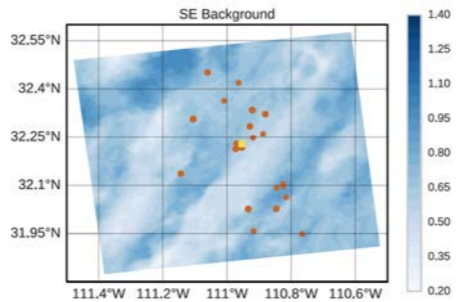


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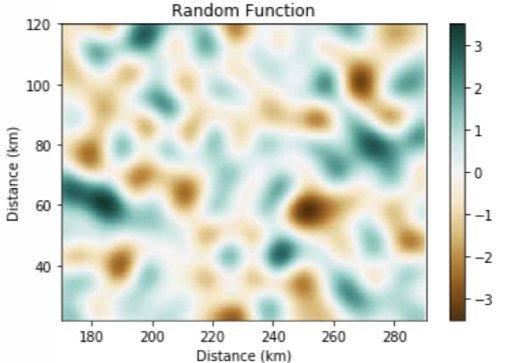
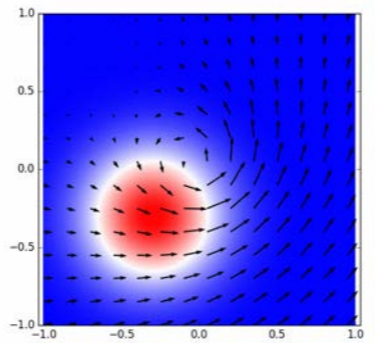
Data



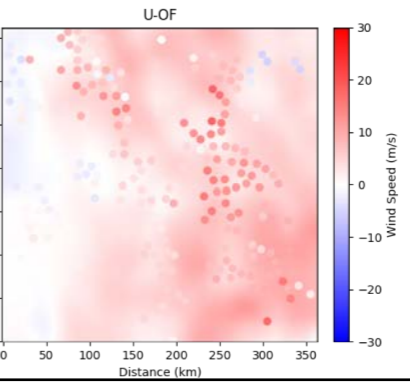
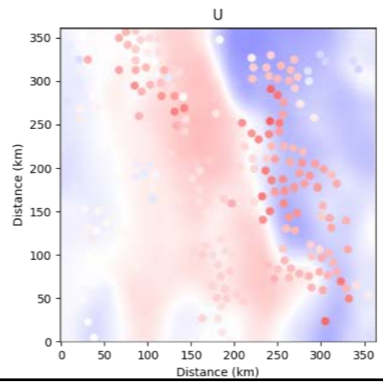
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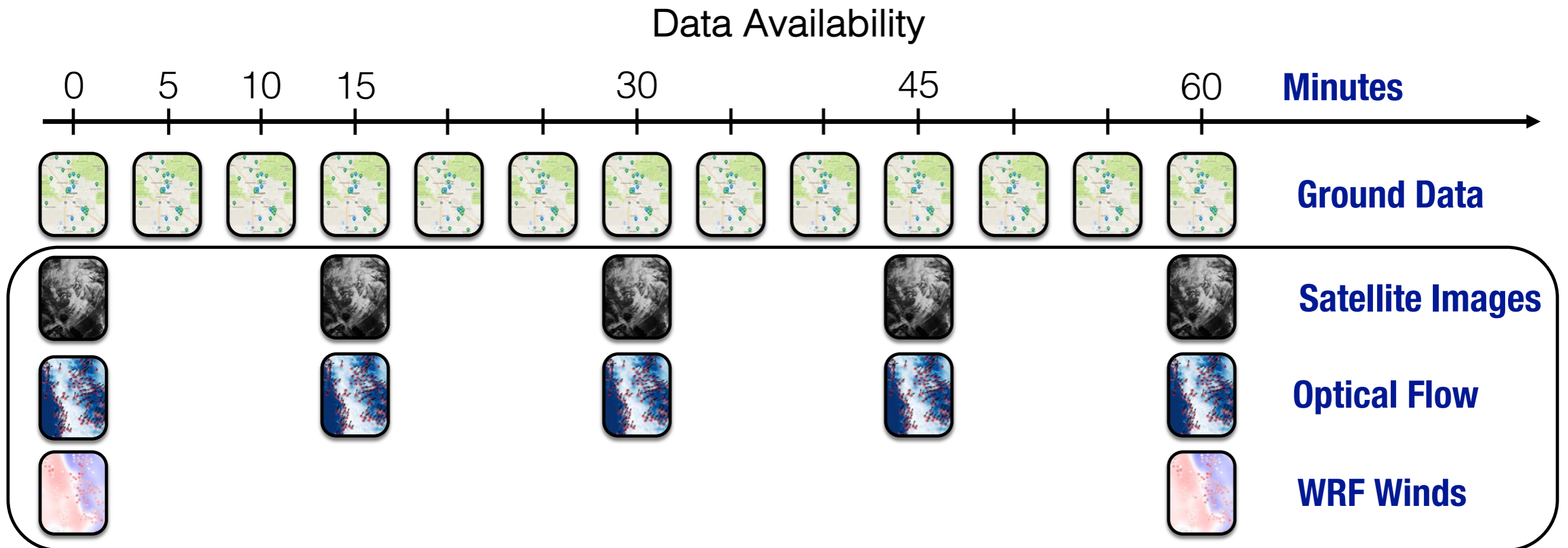
Model & Perturbation



Assimilation

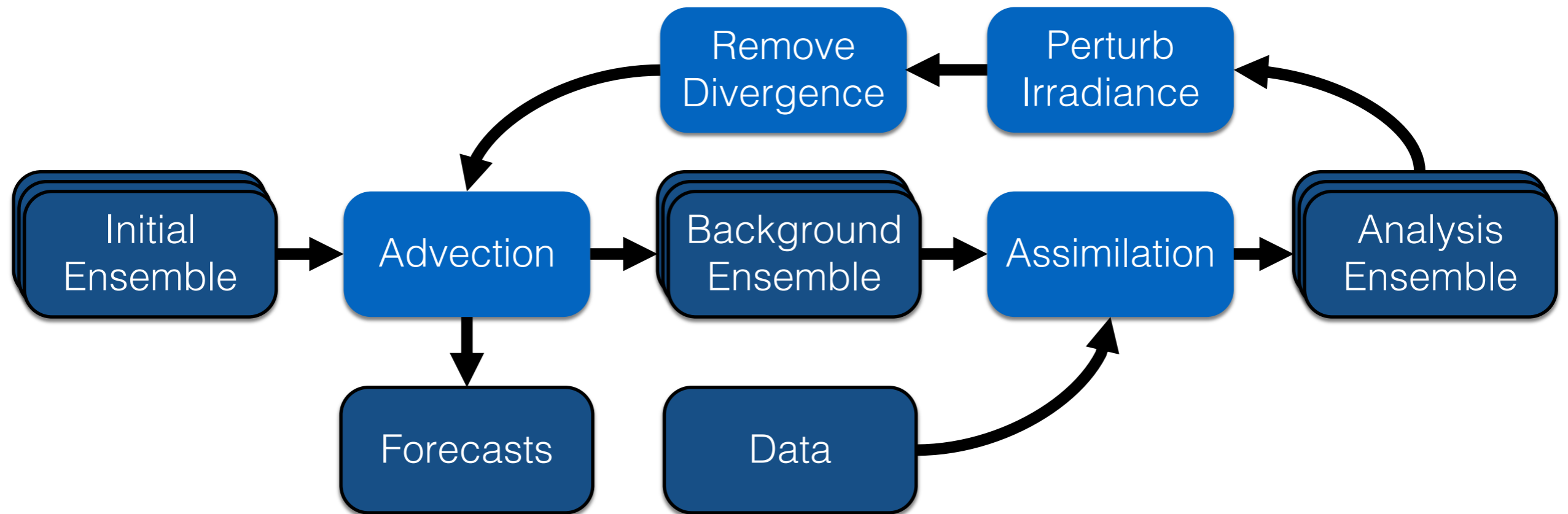


Data summary



- Ground data is available every 5 minutes
- Satellite data are available every 15 minutes (5 minutes with GOES-17)
- Optical flow vectors are available with every new satellite image
- Wind fields coming from numerical weather prediction are available every hour

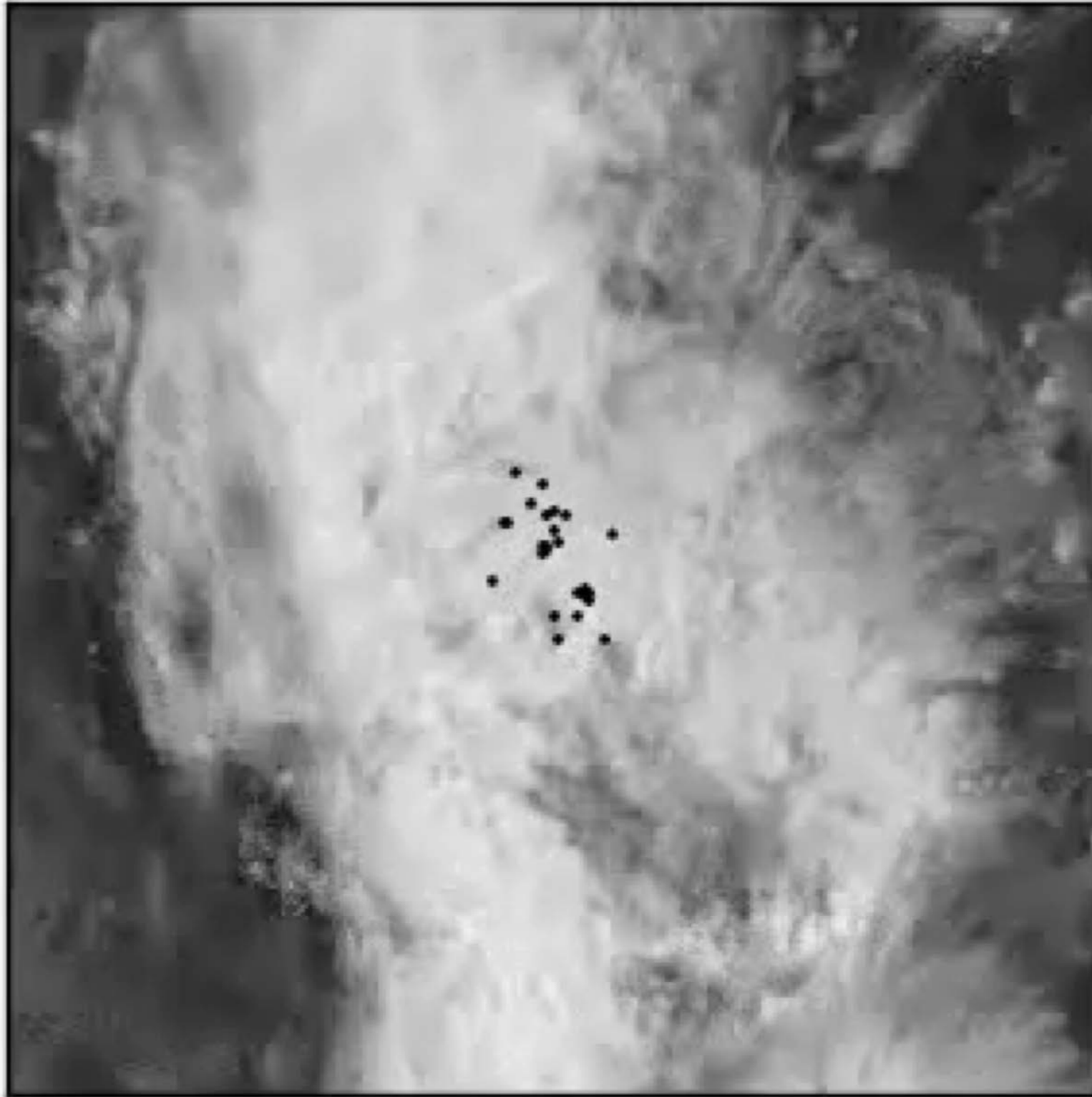
Forecast system



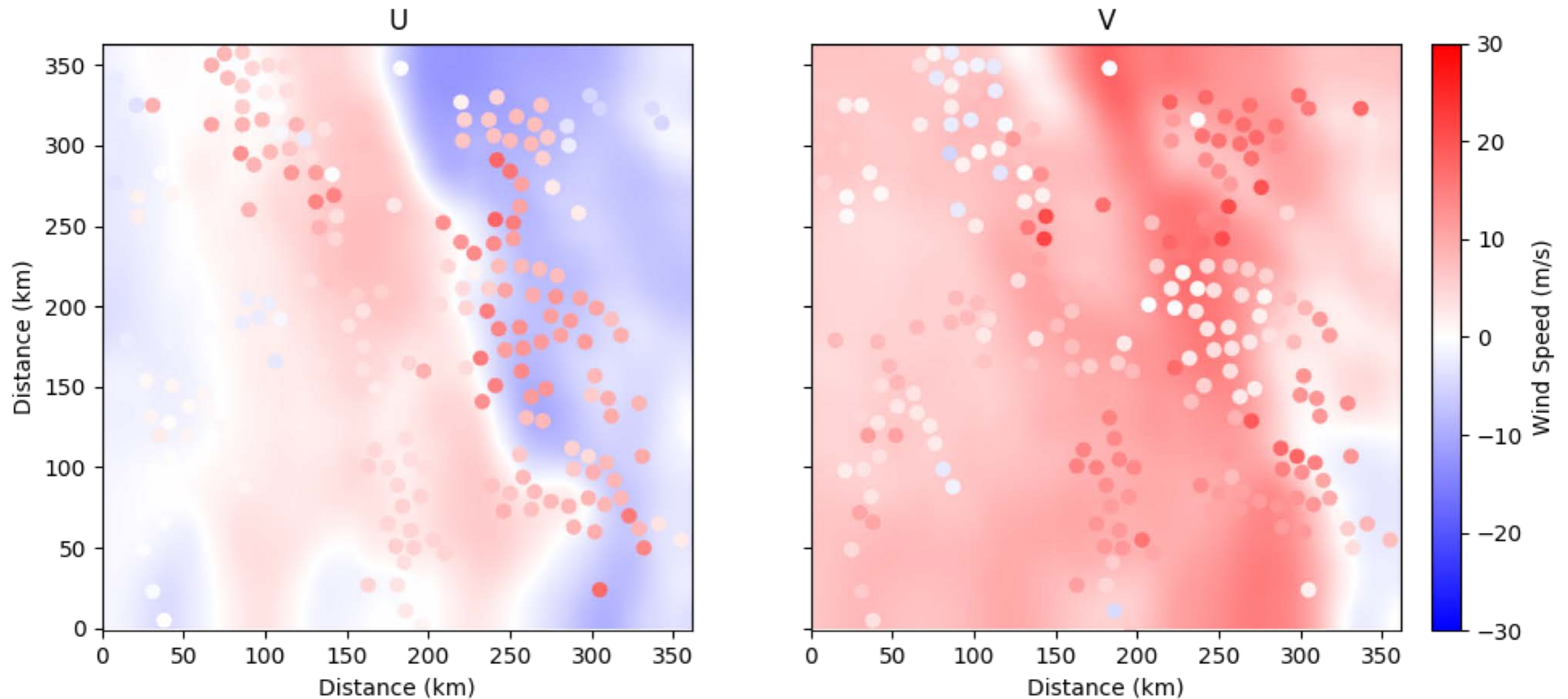
- Each ensemble member has unique cloud field and cloud motion field
- The LETKF is used to assimilate large amounts of observations such as when assimilating WRF wind fields
- The EnKF is used to assimilate small amounts of observations such as sparse optical flow

(eg. Hunt et al., 2007)(eg. Burges et al., 1998)

An example day: May 29th 2014

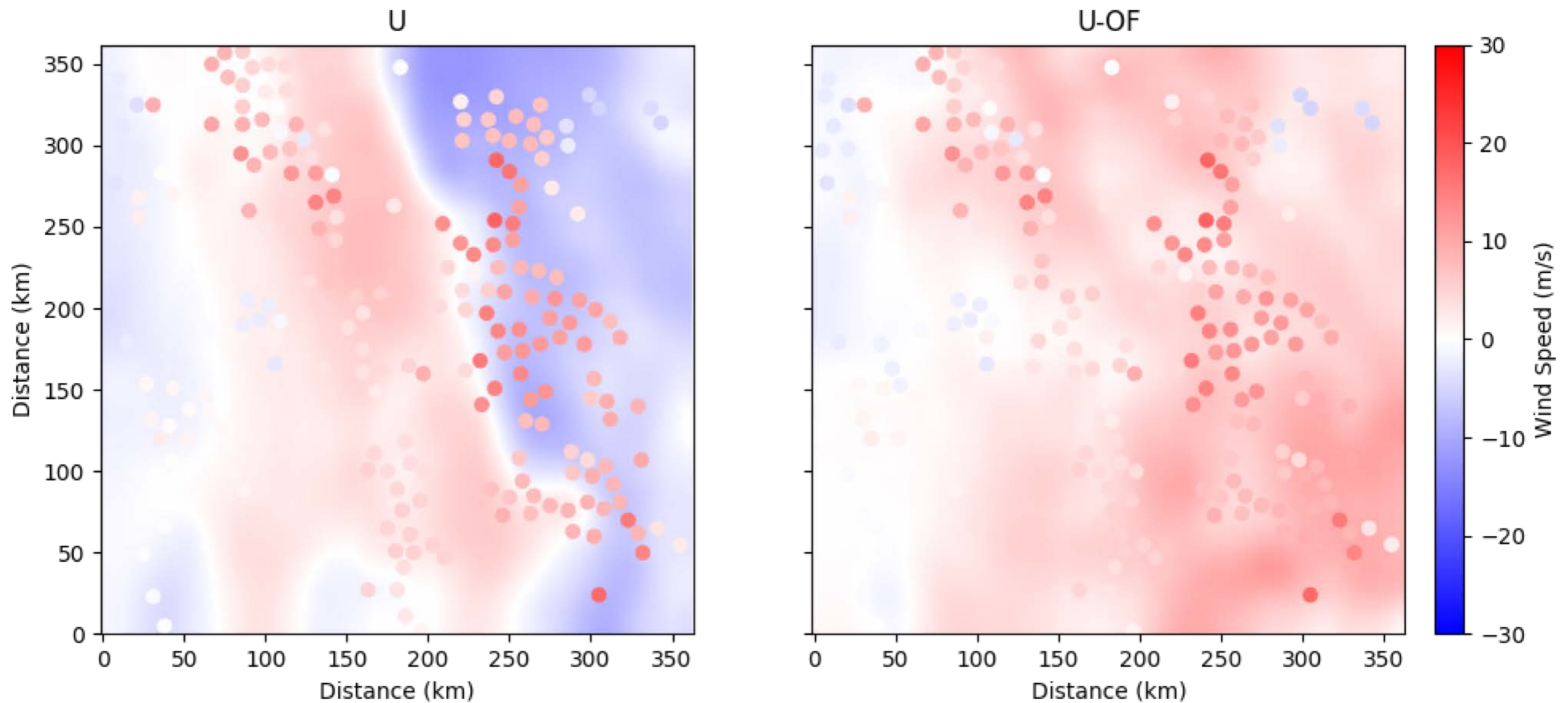


Wind observation



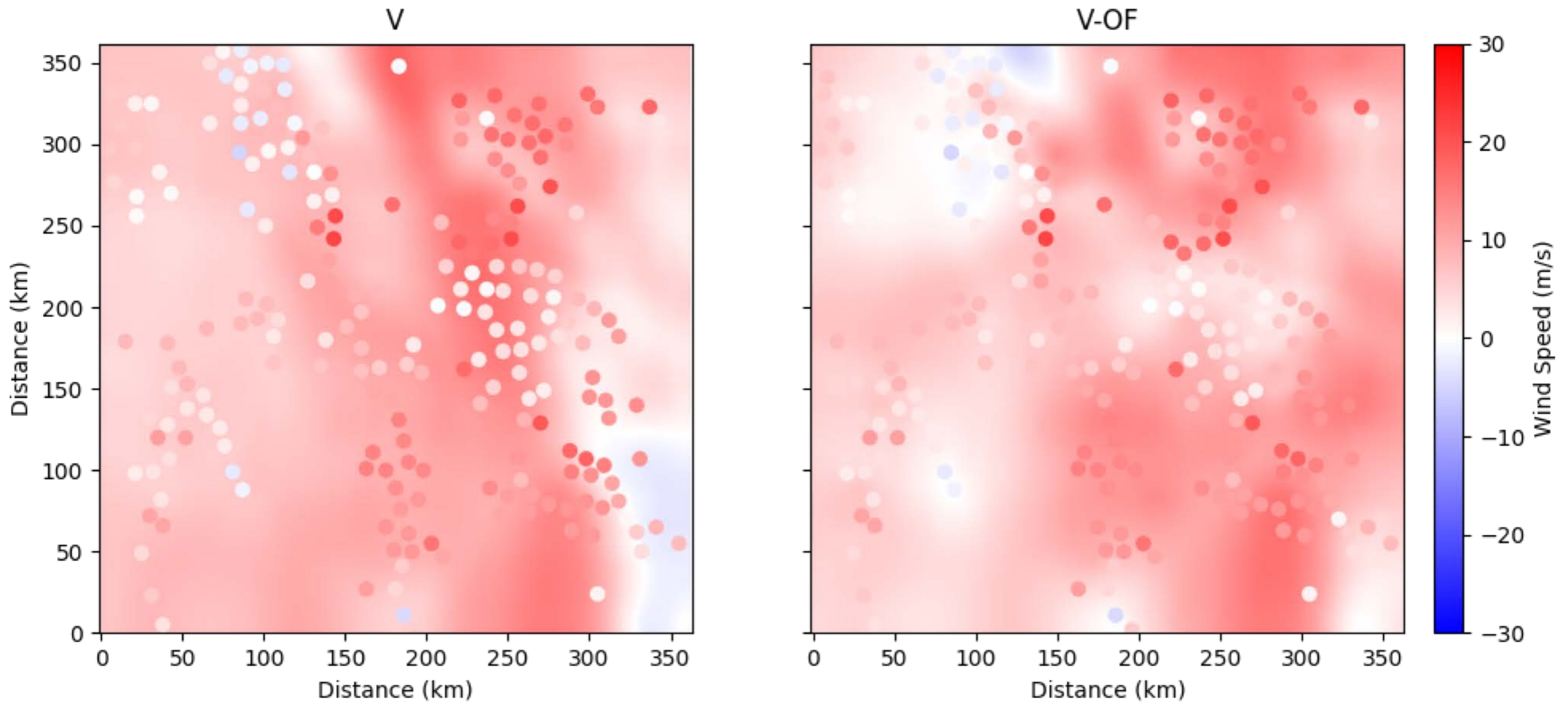
- The resulting vectors (scatter plot) can be thought of as observations of the cloud motion field
- These can then be assimilated into the cloud motion field derived from a numerical weather model (background)

Assimilate optical flow data



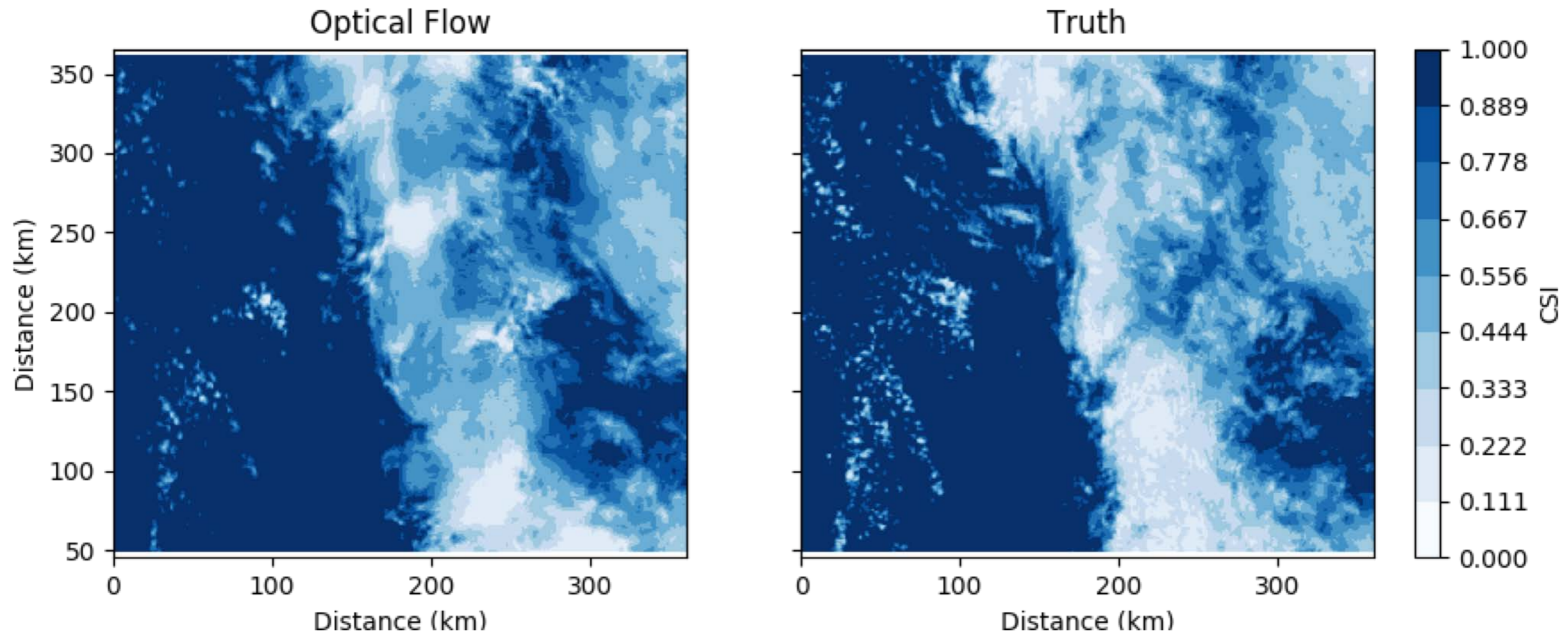
- Assimilate optical flow to improve cloud motion field
- The analysis cloud motion field has greater agreement with our optical flow vectors

Assimilate optical flow data



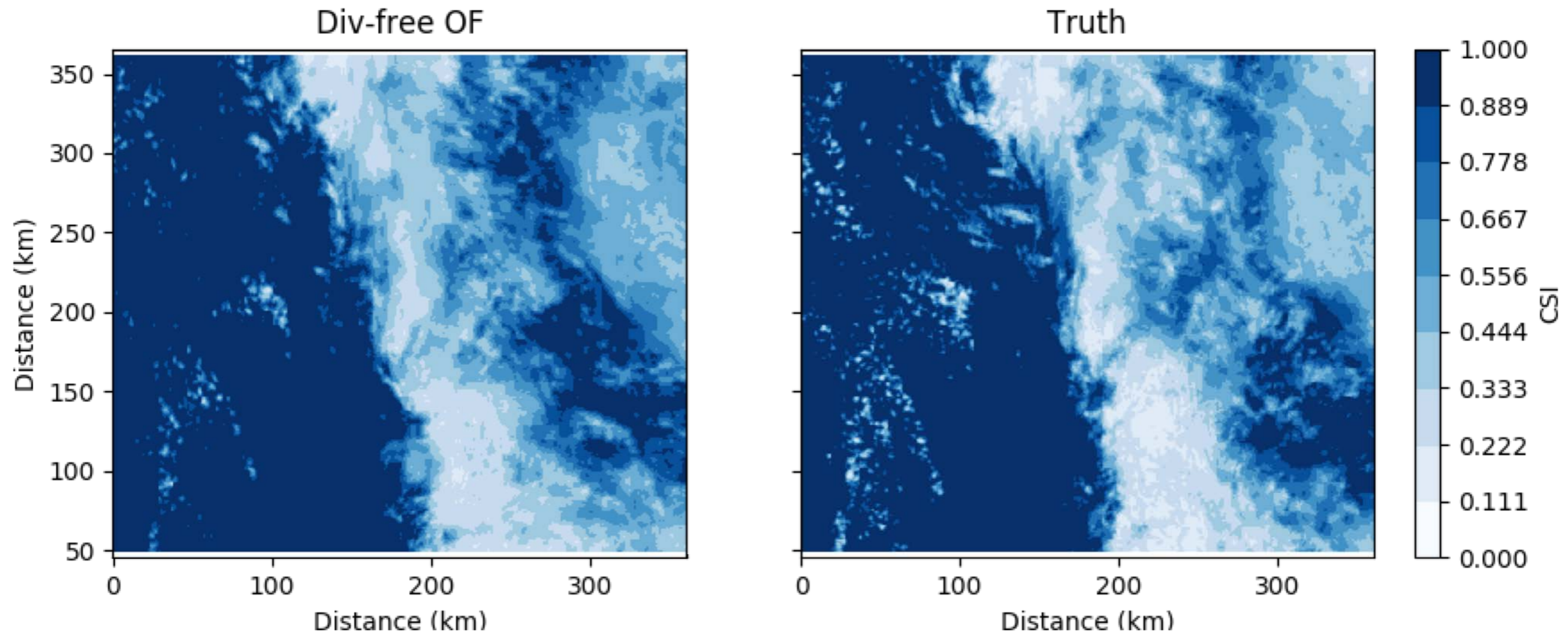
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Forecasting with optical flow



- Assimilate optical flow to improve wind field
- Removal of divergence further reduces error and improves

Forecasting with optical flow



- Assimilate optical flow to improve wind field
- Removal of divergence further reduces error and improves

Remove divergence with Poisson's equation

Isolate portion of vector field with non-zero divergence

$$\vec{V} = -\nabla\phi + \tilde{V}$$

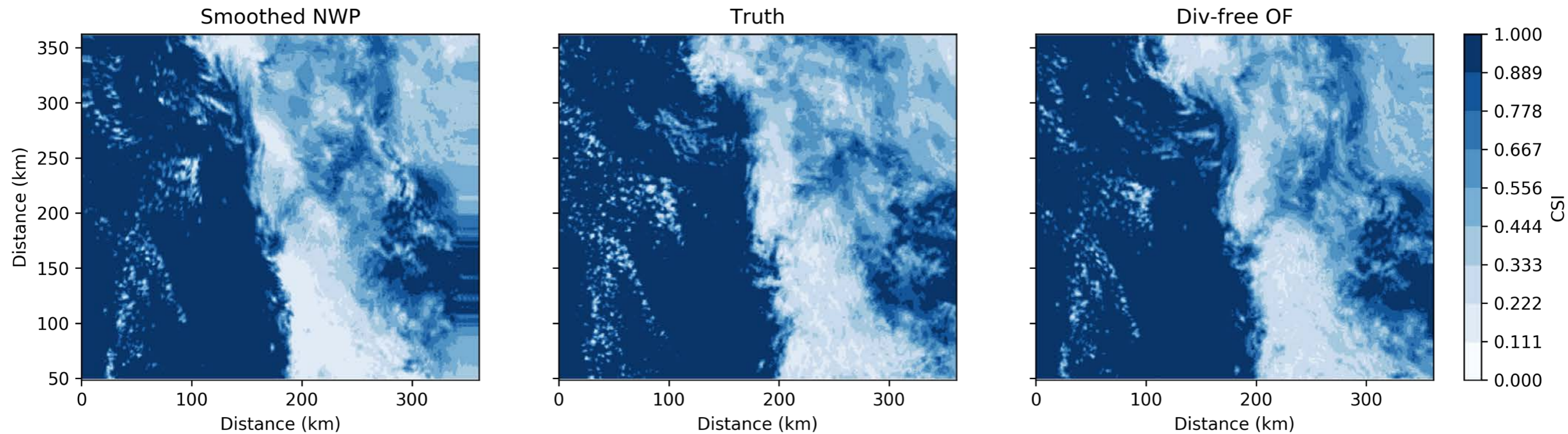
$$\nabla \cdot \vec{V} = -\nabla^2\phi$$

$$\vec{n} \cdot \nabla\phi = 0 \text{ on } \partial\Omega$$

Advect only using the portion of the vector field with zero divergence

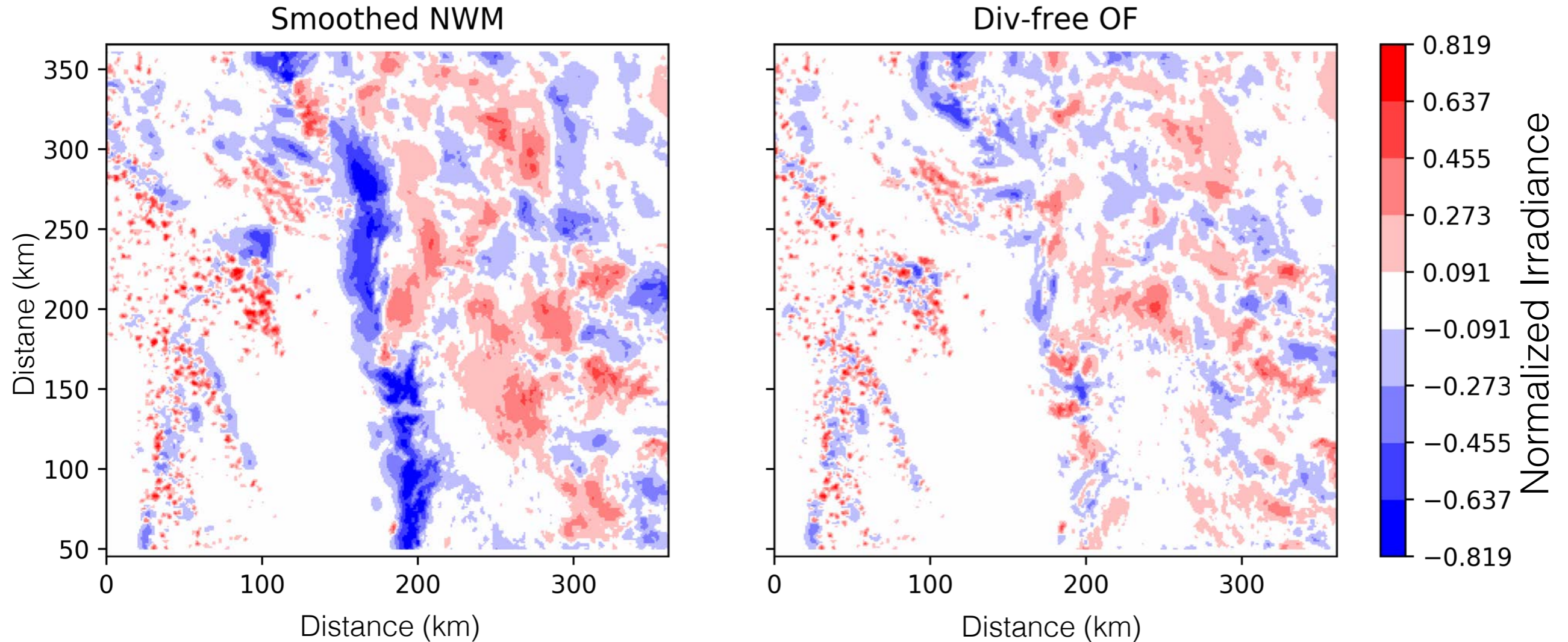
$$\tilde{V} = \vec{V} + \nabla\phi$$

Forecasting with and without assimilation



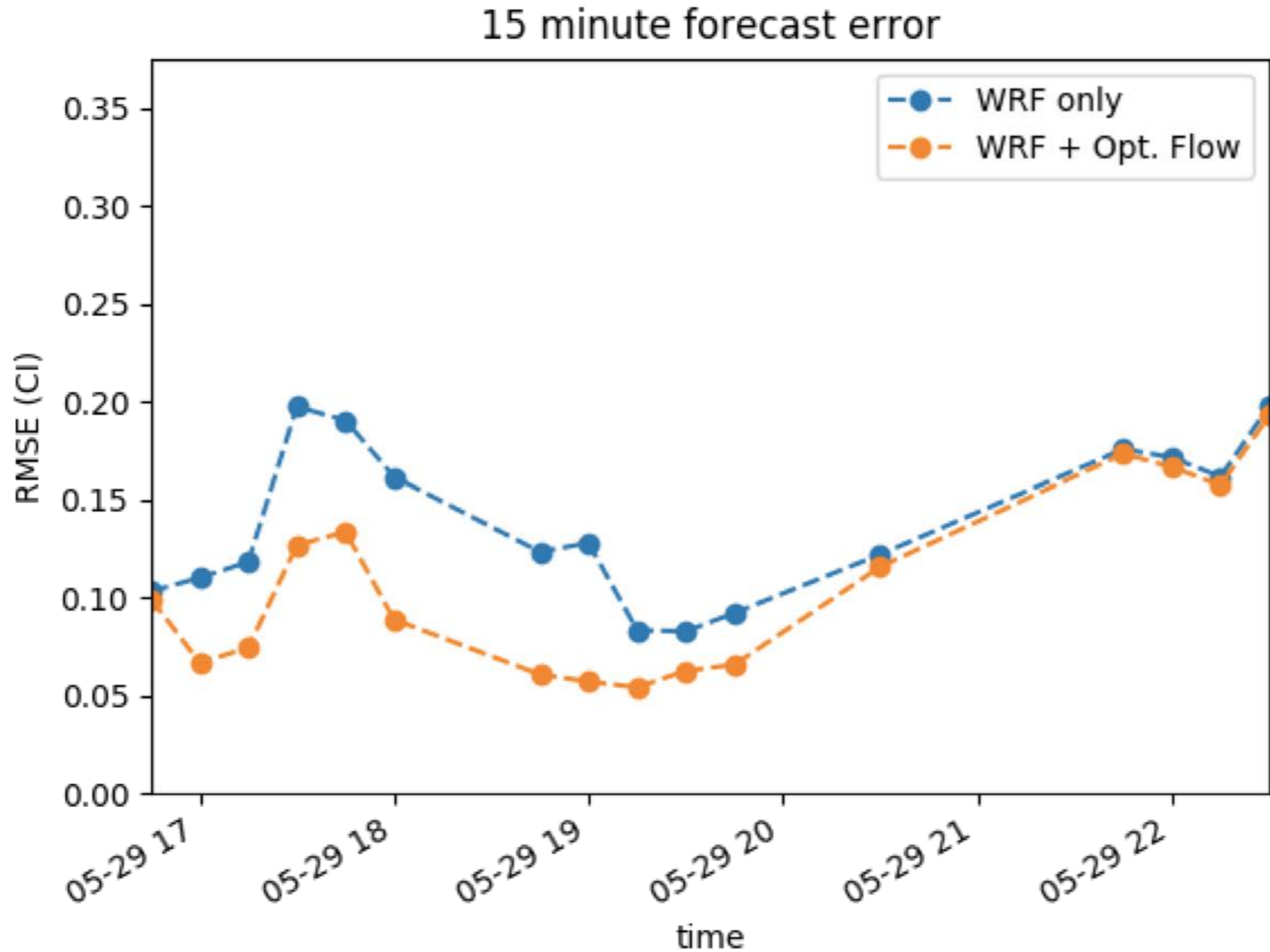
- Comparison of forecasts derived from Numerical Weather Prediction cloud motion and with optical flow vectors assimilated.
- Error is reduced when optical flow vectors are assimilated
- A large portion of error reduction come from correct cloud front position

Forecasting with and without assimilation



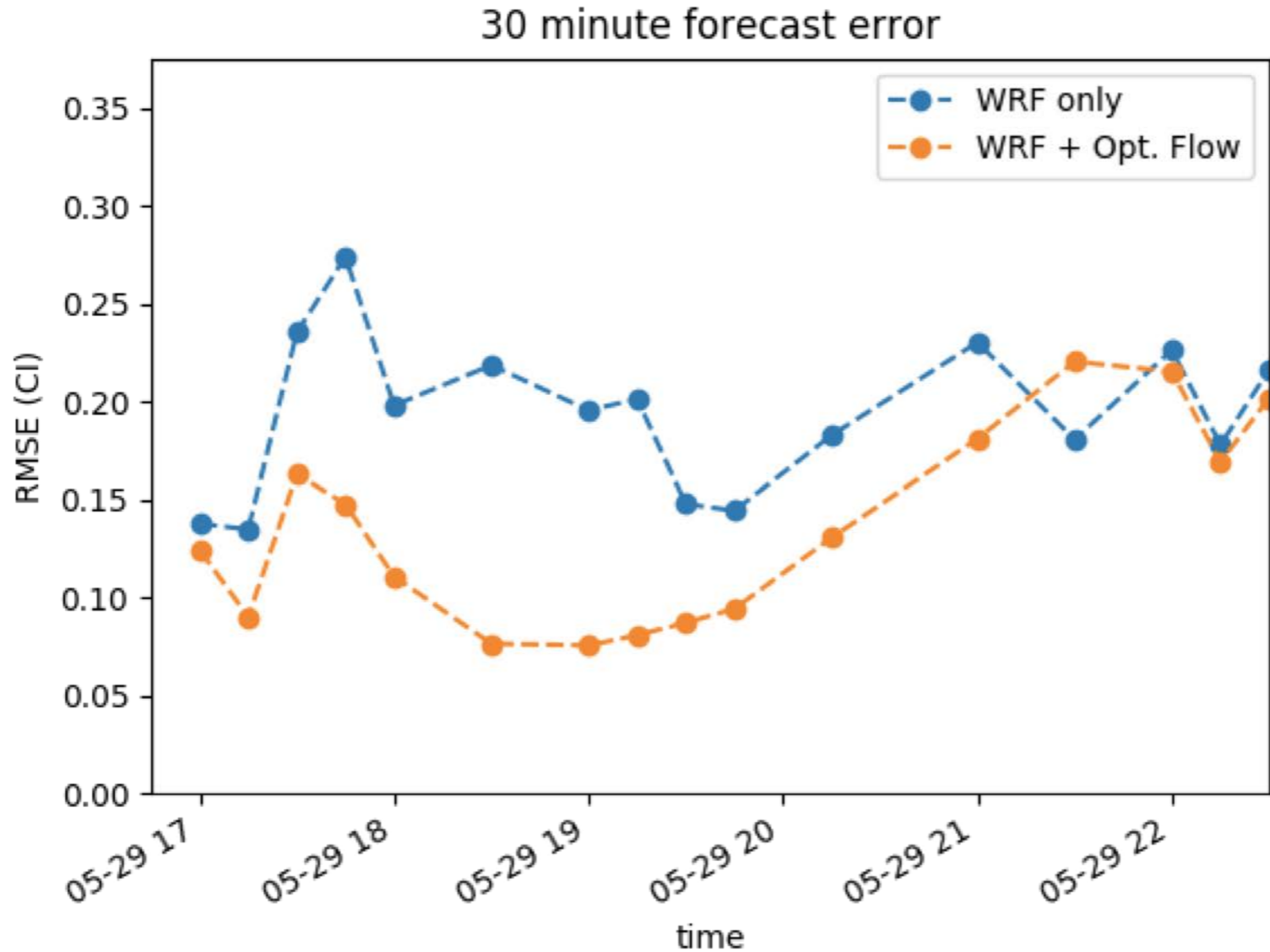
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Error time series



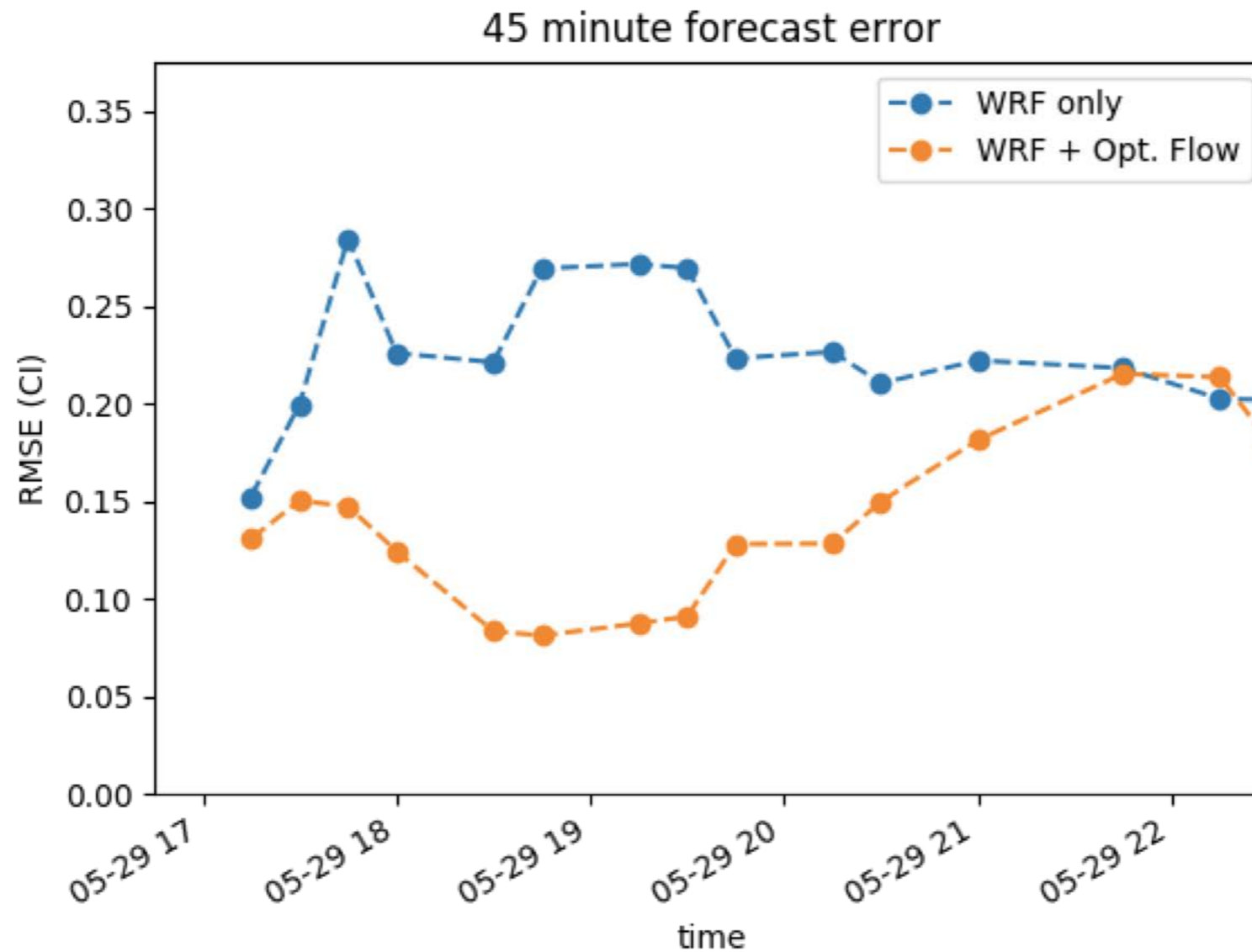
Error is calculated as RMSE between forecasted normalized irradiance and the actual satellite derived normalized irradiance for a 2240 km² area over Tucson.

Error time series



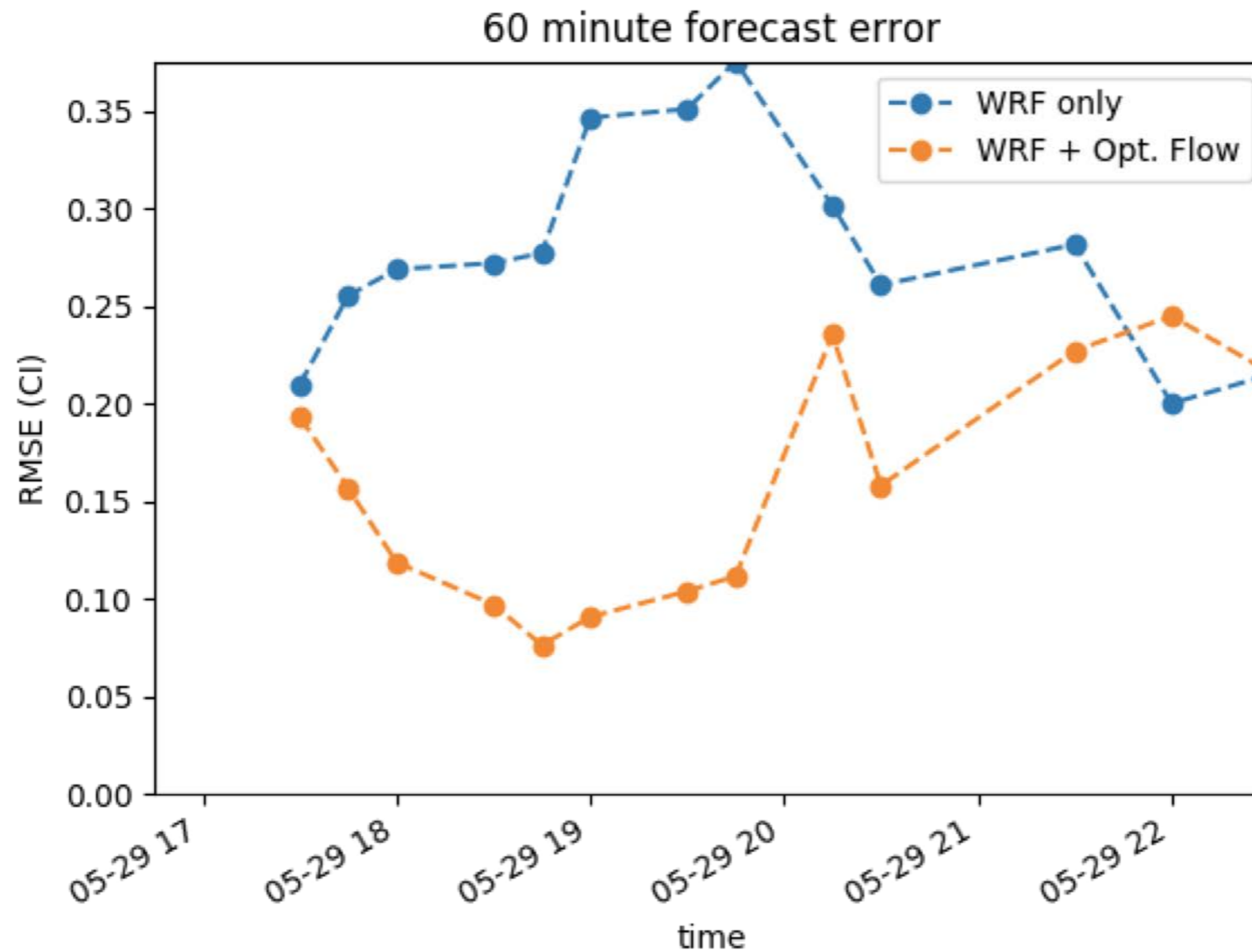
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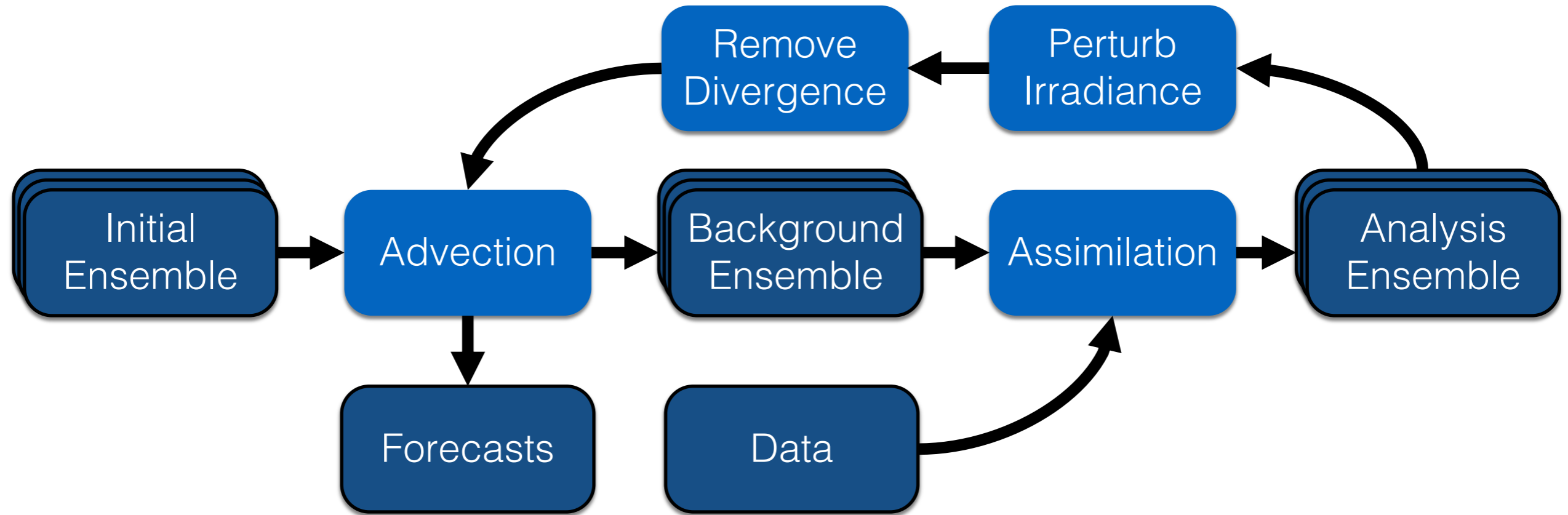
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Error time series



Error is calculated as RMSE between forecasted normalized irradiance and the actual satellite derived normalized irradiance for a 2240 km² area over Tucson.

Summary



- Short term irradiance forecasts through combining data from satellites, ground sensors, numerical weather prediction, and optical flow
- LETKF allows us to quickly assimilate a large amount of observations
- Assimilation of optical flow introduces convergence which should be removed
- Error is significantly reduced in comparison to using NWP winds alone

Thank you!



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