National Aeronautics and Space Administration

Estimating Daily High-Resolution Vegetation Index to Support ECOSTRESS Evapotranspiration Processing

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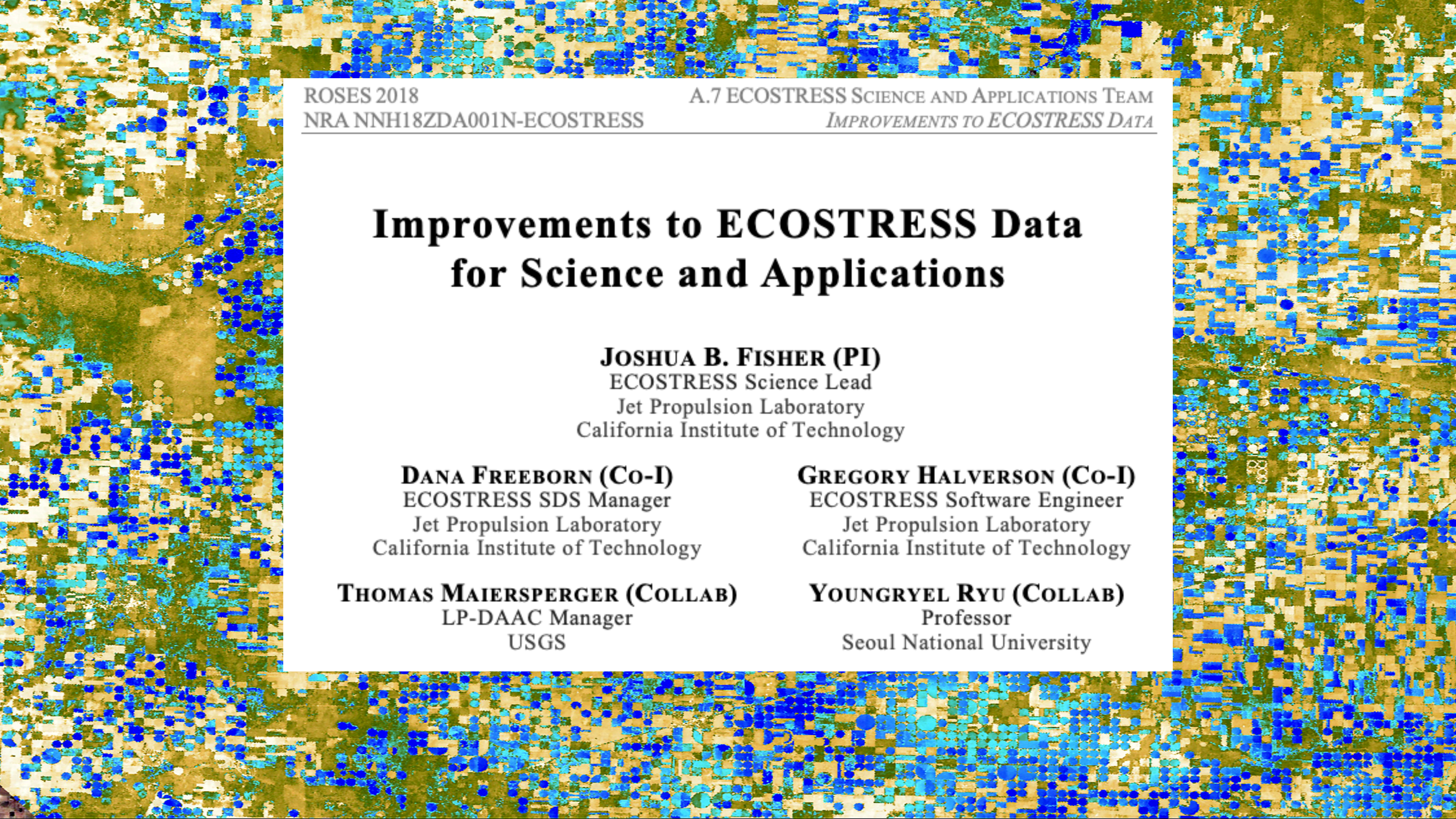

Improvements to ECOSTRESS Data for Science and Applications

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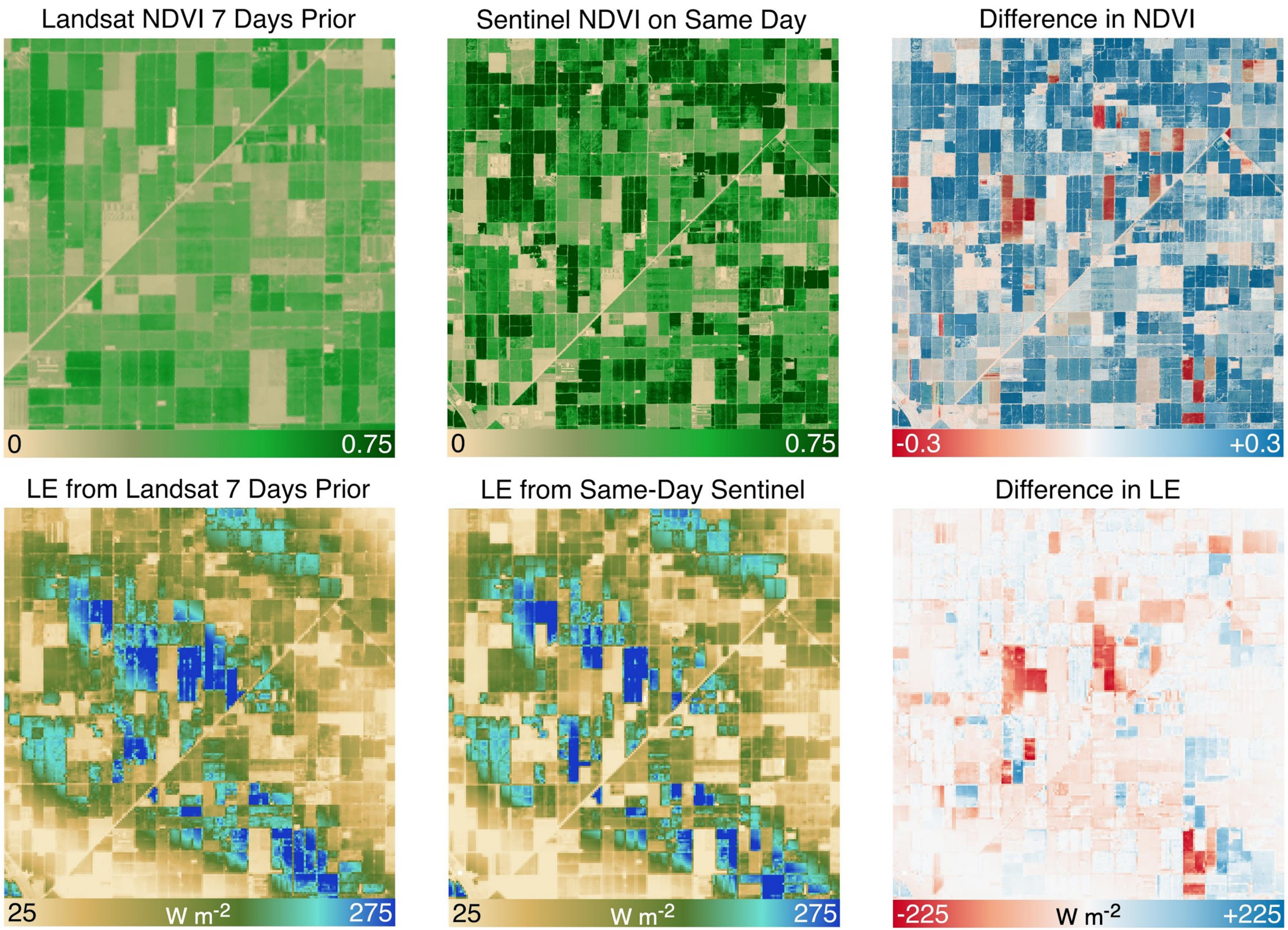
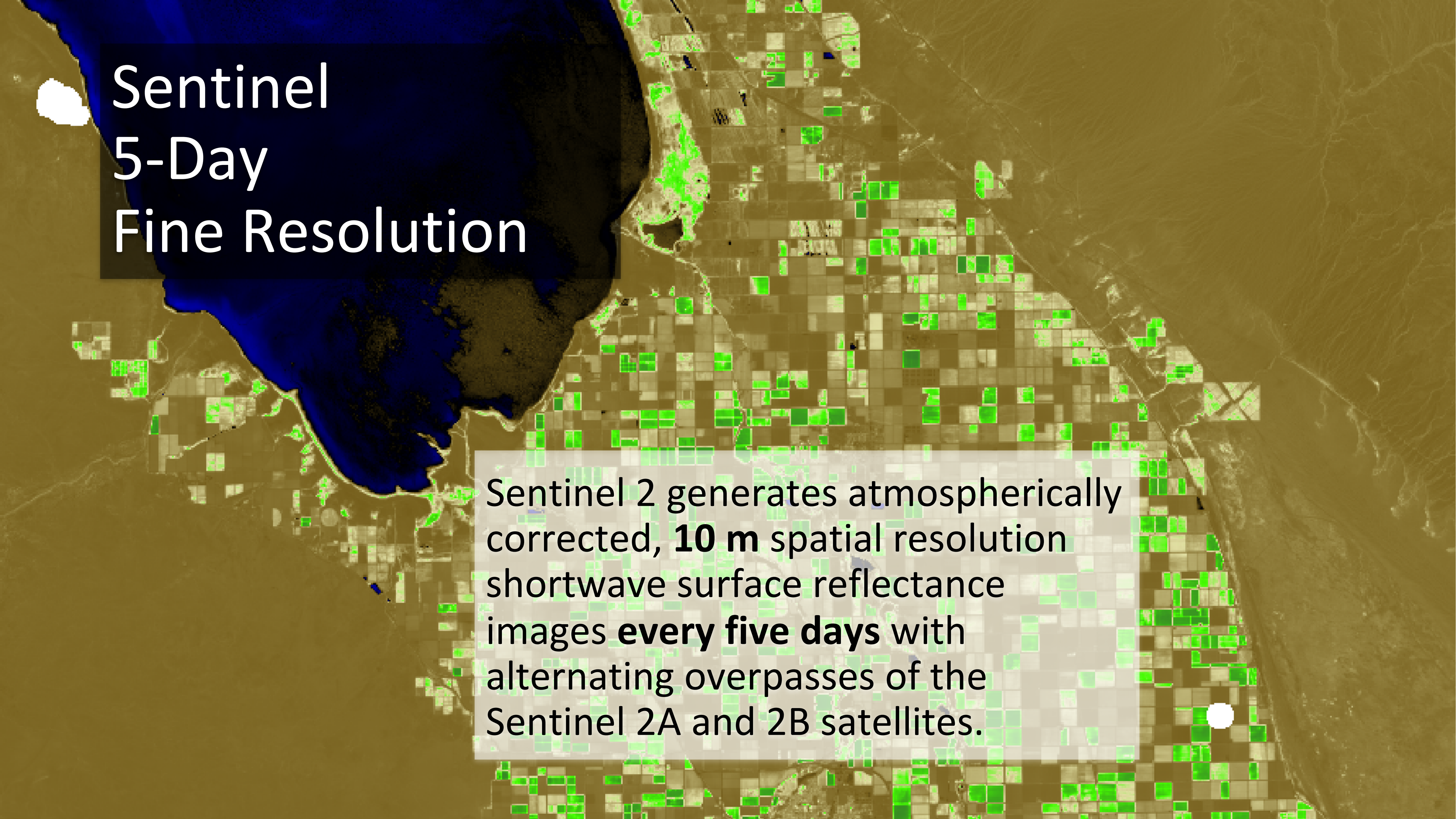
Remote Sensing of ET Requires Co-Incident NDVI

A major challenge in estimating evapotranspiration from ECOSTRESS surface temperature is the lack of co-incident NDVI.

Irrigated agriculture produces abrupt changes in the amount of vegetation on the ground during green-up and harvest.

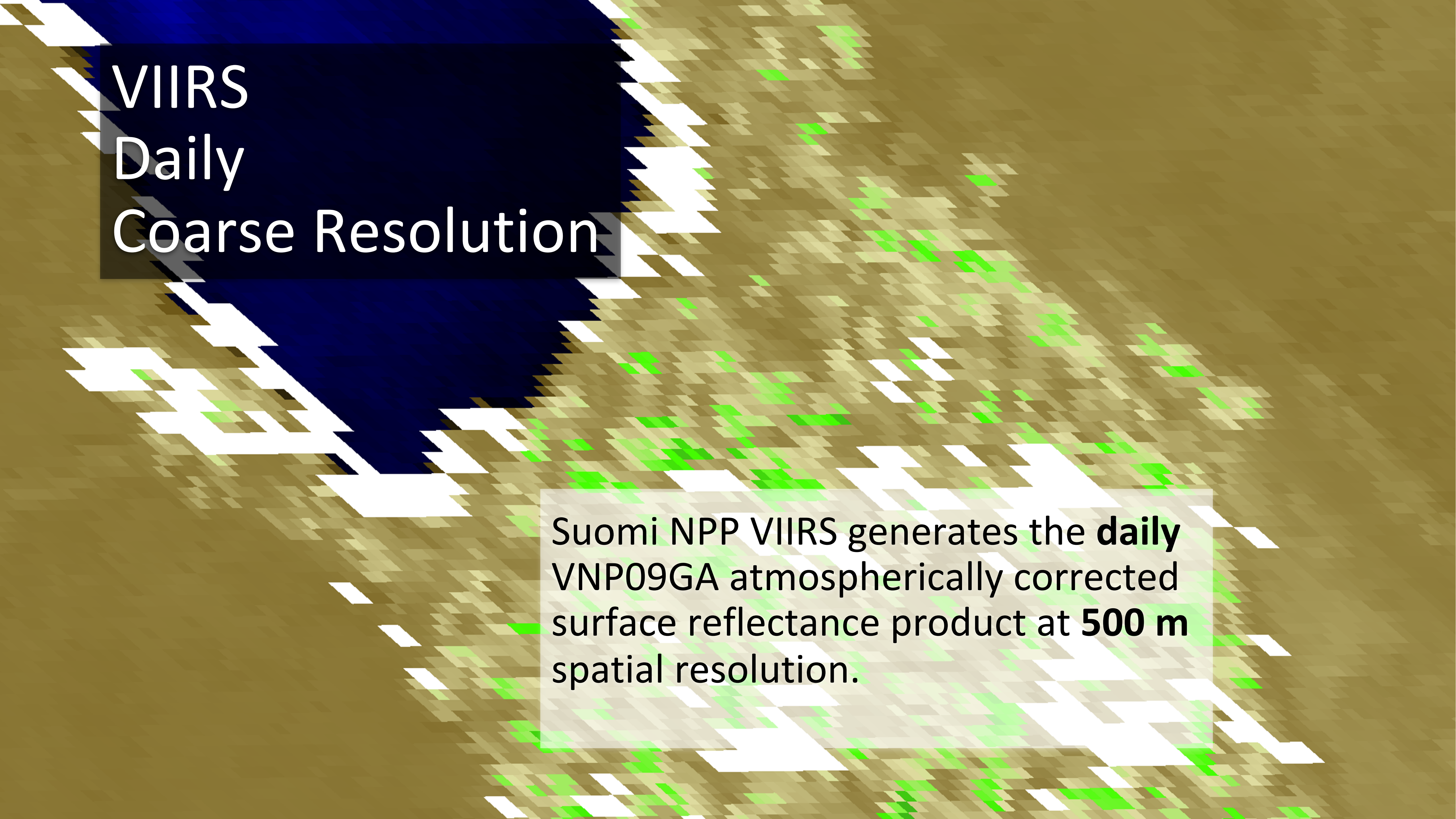
If the most recent high-resolution image of NDVI was acquired before agricultural changes and the surface temperature image was acquired after, this can result in significant error in ET.

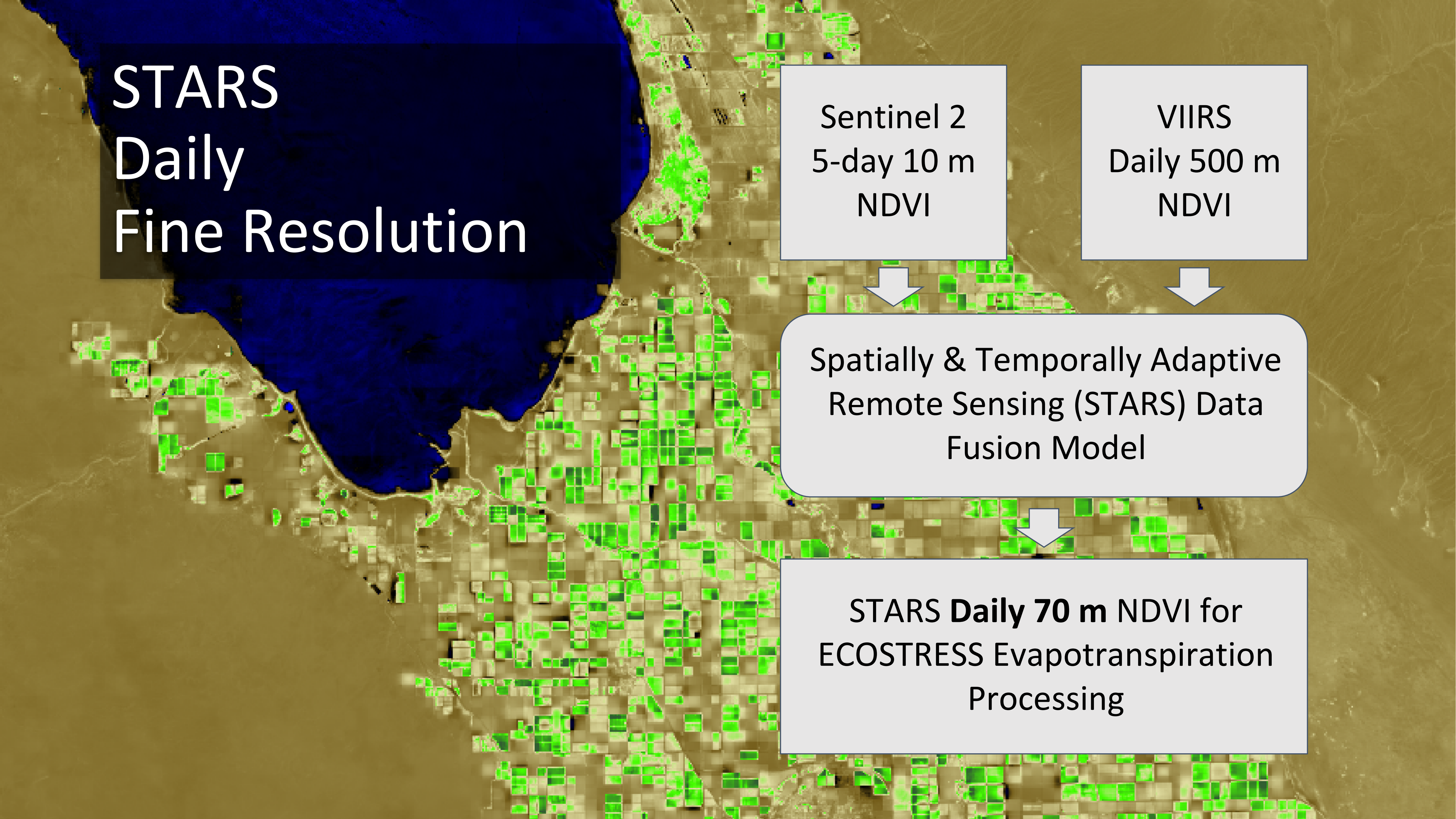


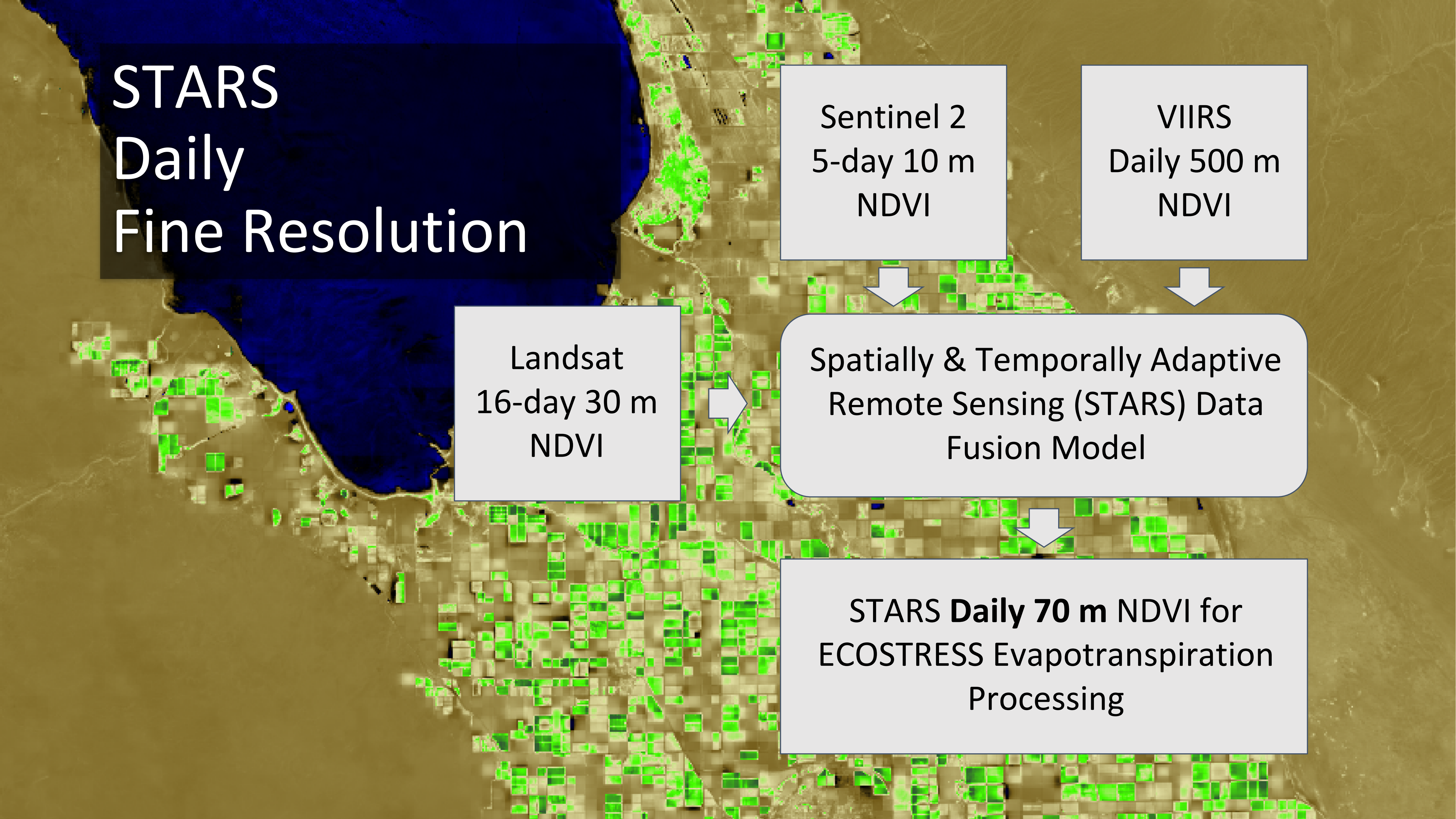


Sentinel
5-Day
Fine Resolution

Sentinel 2 generates atmospherically corrected, **10 m** spatial resolution shortwave surface reflectance images **every five days** with alternating overpasses of the Sentinel 2A and 2B satellites.


VIIRS
Daily
Coarse Resolution
Suomi NPP VIIRS generates the **daily** VNP09GA atmospherically corrected surface reflectance product at **500 m** spatial resolution.


STARS
Daily
Fine Resolution
Sentinel 2
5-day 10 m
NDVI
VIIRS
Daily 500 m
NDVI
Spatially & Temporally Adaptive
Remote Sensing (STARS) Data
Fusion Model
STARS **Daily 70 m** NDVI for
ECOSTRESS Evapotranspiration
Processing


STARS
Daily
Fine Resolution
Sentinel 2
5-day 10 m
NDVI
VIIRS
Daily 500 m
NDVI
Landsat
16-day 30 m
NDVI
Spatially & Temporally Adaptive Remote Sensing (STARS) Data Fusion Model
STARS **Daily 70 m** NDVI for ECOSTRESS Evapotranspiration Processing

Multi-sensor Data Fusion

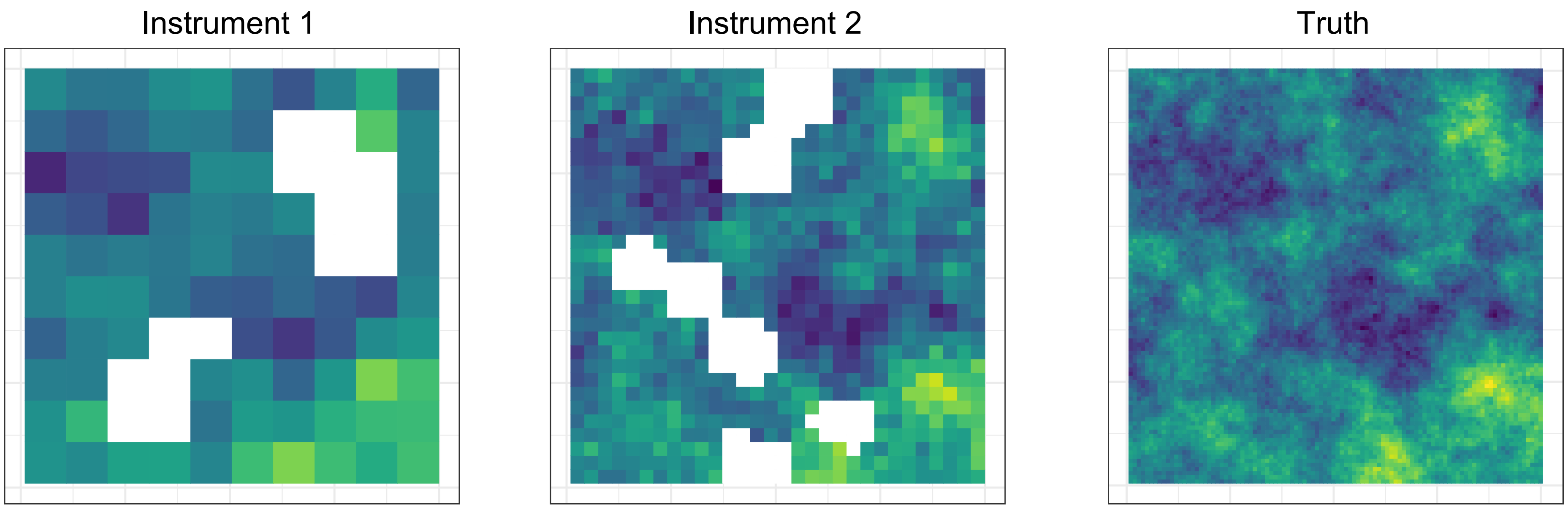
Challenges:

- Highly heterogeneous landcover/terrain
- Large gaps of missing data due to cloud cover and temporal resolution
- Massive, nonstationary spatiotemporal data
- Computational/temporal constraints, "streaming" data fusion

Existing Methods (non-exhaustive):

- STARFM and subsequent variants (e.g. Gao et al. 2006; Zhu et al. 2010)
- Unmixing-based methods (e.g. Gevaert, et al. 2011)
- Spatial/spatiotemporal statistical models (e.g. Nguyen, et al. 2012, 2014; Ma and Kang, 2020; Johnson, et al., 2020+)

Spatiotemporal Statistical Data Fusion



Assume for a generic grid cell, *G*, the observed products are a, noisy spatial aggregate of the underlying true process:

$$y_t^k(G) = \frac{1}{|\mathcal{D} \cap G|} \left\{ \sum_{i \in \mathcal{D} \cap G} \eta_{it} \right\} + v^k(G), \quad v^k(G) \sim \mathcal{N}(0, \sigma_t^2(G)^k)$$

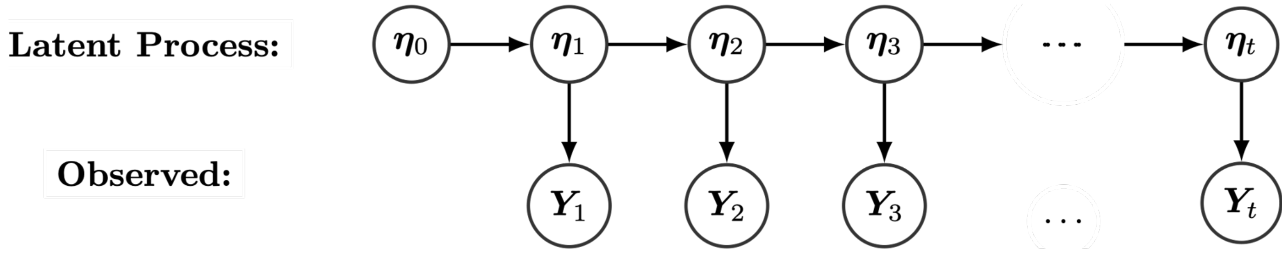
- $\{\eta_{it} : i \in D\}$ is the latent spatial process on a discretized domain made up of N fine-scale, non-overlapping pixels
- Does not require images to be downscaled pre-fusion!

Gap-filling through latent, spatiotemporal model

Model the unknown, high-resolution product of interest, η_{it}, as a spatiotemporal process.

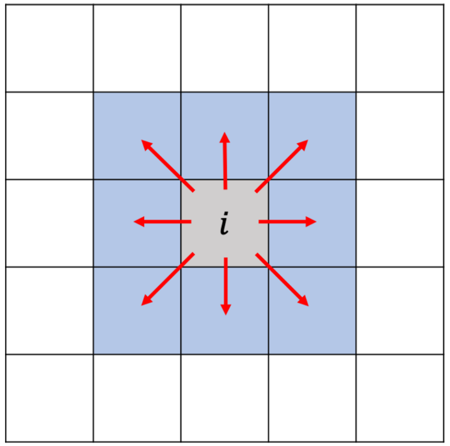
For each pixel, i,

$$\eta_{it} = \eta_{i,t-1} + \omega_{it}$$

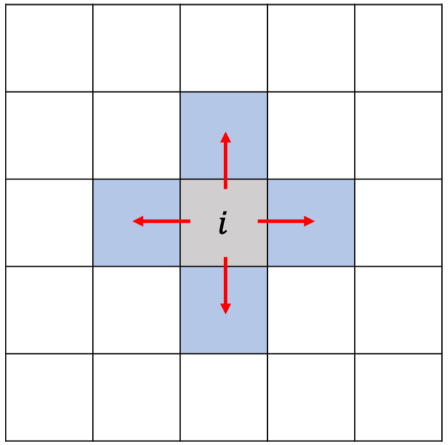


where ω_{it} follow a conditionally autoregressive (CAR) model

$$\omega_{it} | \boldsymbol{\omega}_{-it} \sim \mathcal{N}\left(\phi \sum_{j \sim N_i} c_{ij}\, \omega_{jt},\ \tau_{it}^{-1}\right)$$



Queen's neighborhood

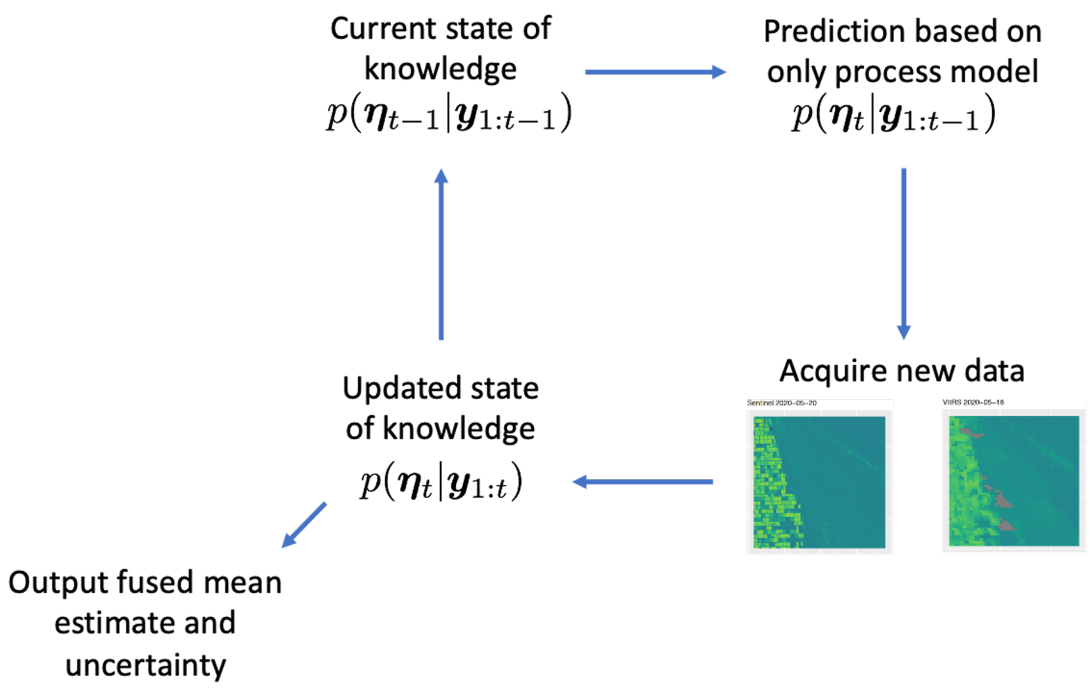


Rook's neighborhood

Fast Estimation via Local Kalman Filtering

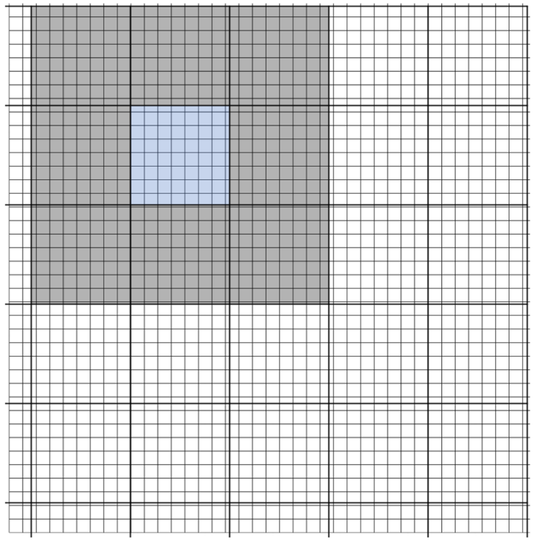
The estimate of a daily, high-resolution product is obtained as the posterior mean of the distribution $p(\eta_t | y_t, y_{t-1} \dots y_1)$.

Online fusion via Kalman Filtering



Fast, moving window estimation

Fit fusion model to a local subset of pixels defined by a rook or queen neighborhood structure on the coarse image



Can exploit embarrassingly parallel computation, reduces computational cost from $O(n_f^3)$ operations to $O(n_c m^3)$ -- linear in number of coarse resolution pixels

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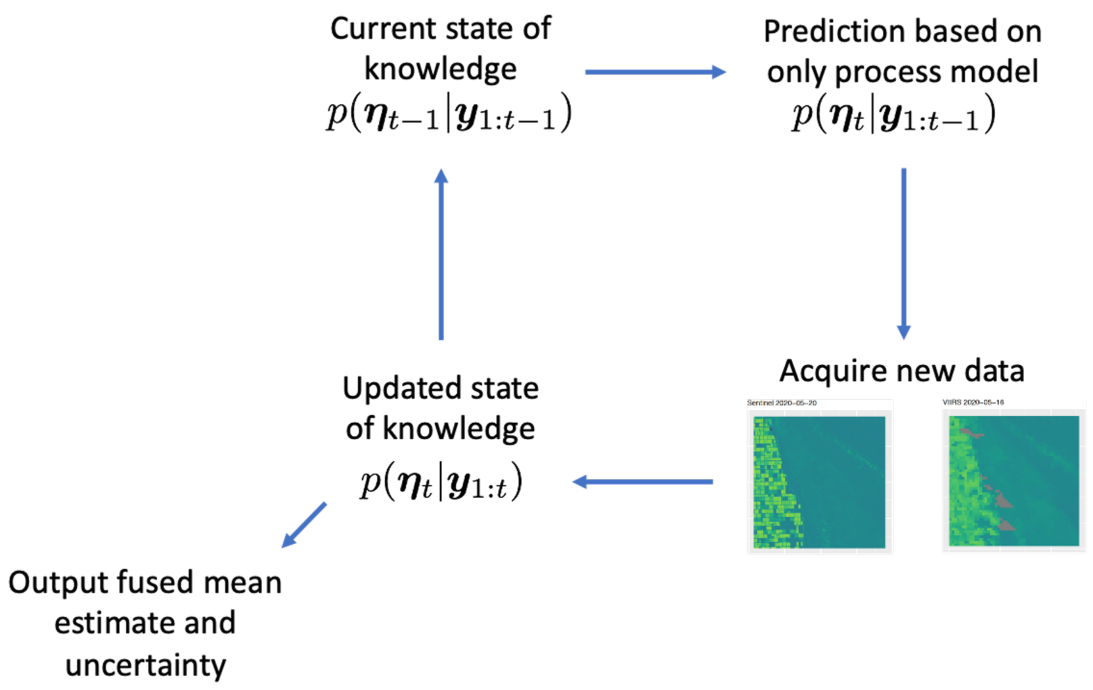

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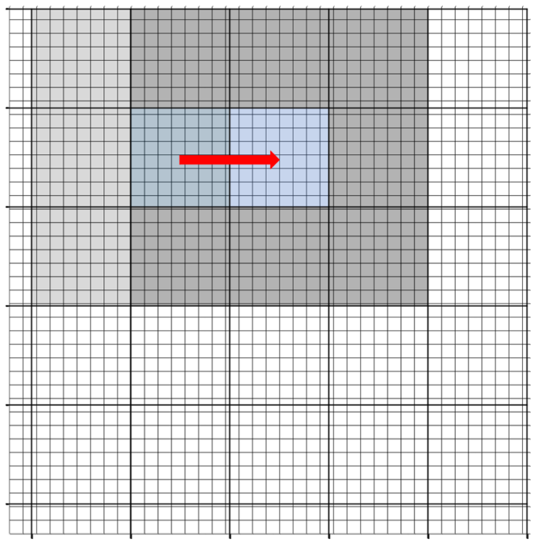
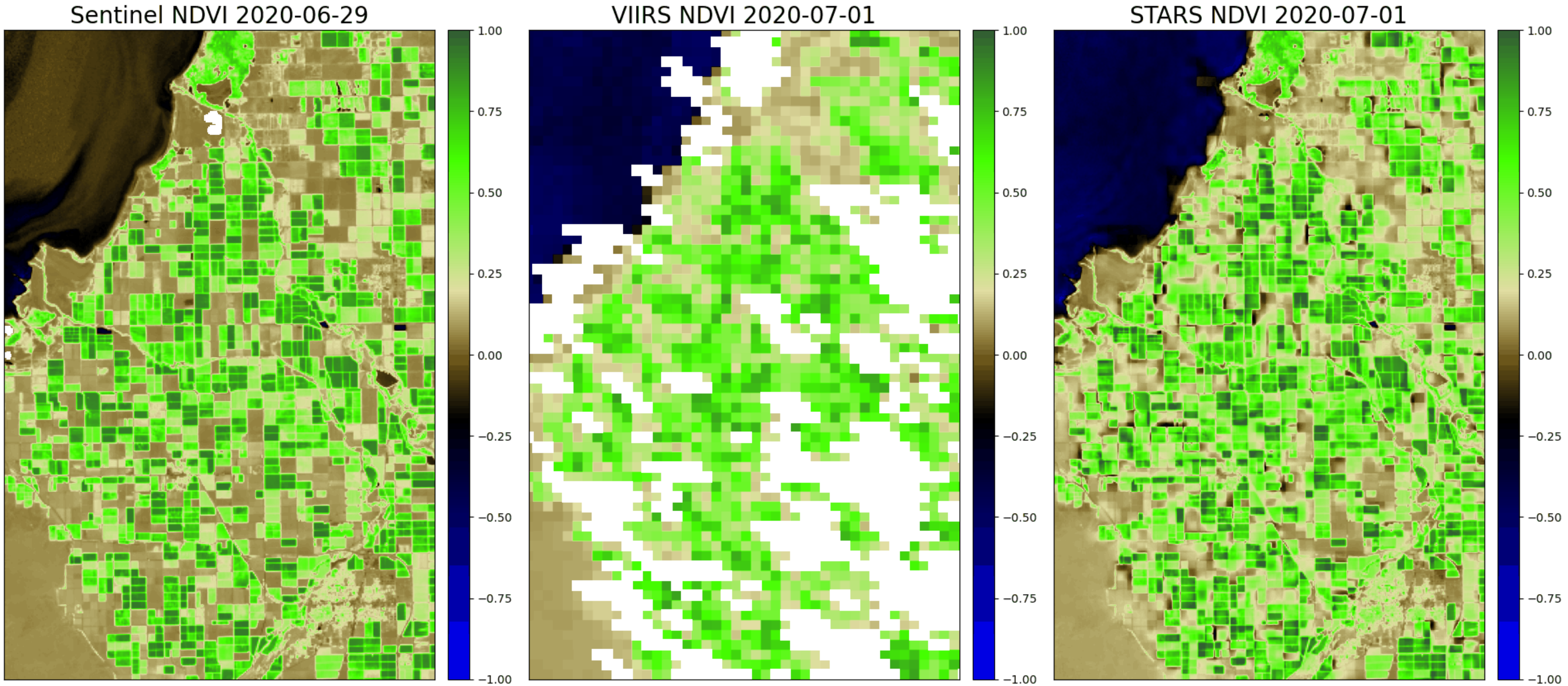


Example VIIRS-Sentinel 70m Data Fusion



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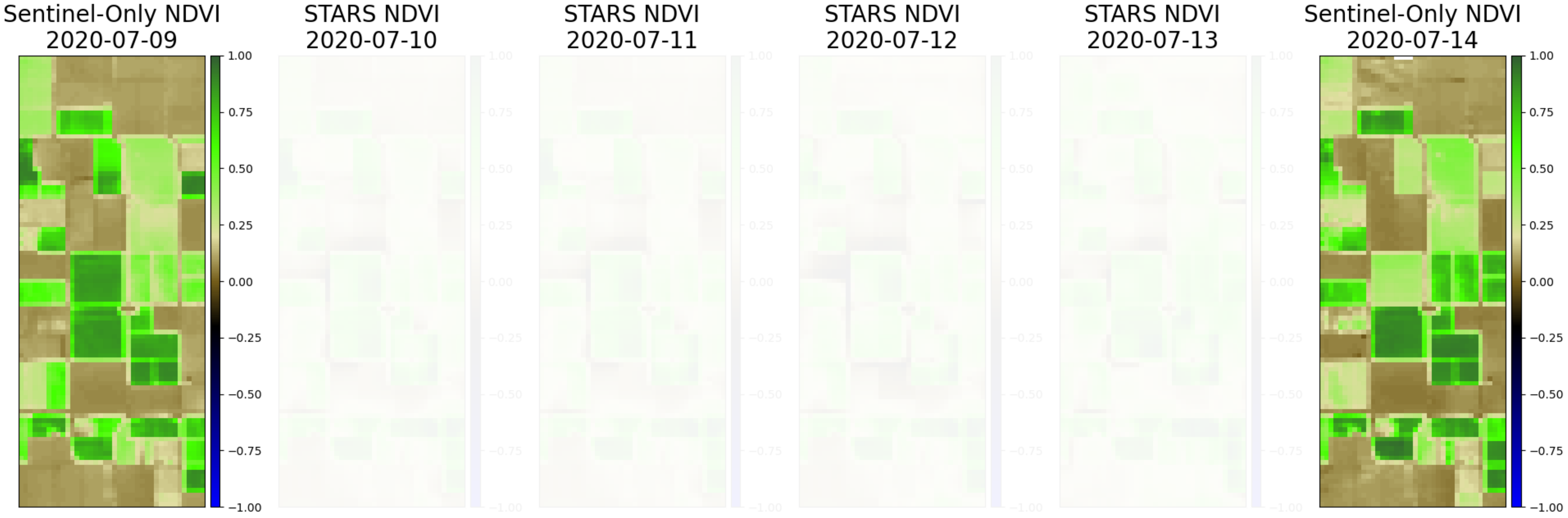

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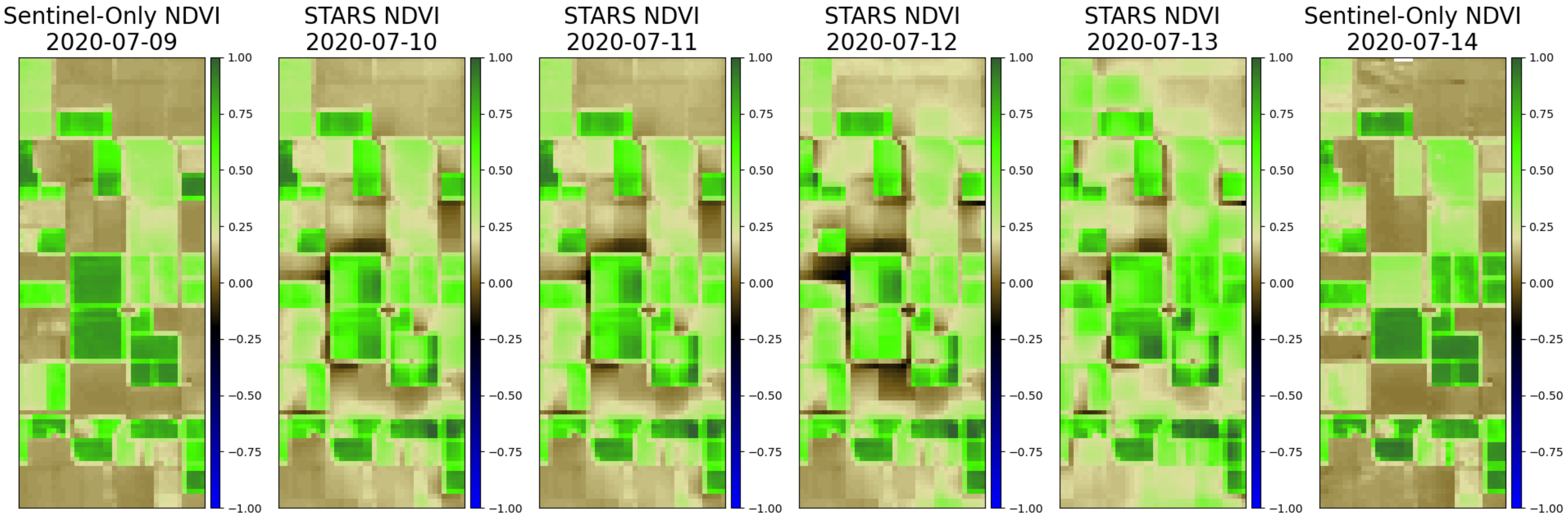

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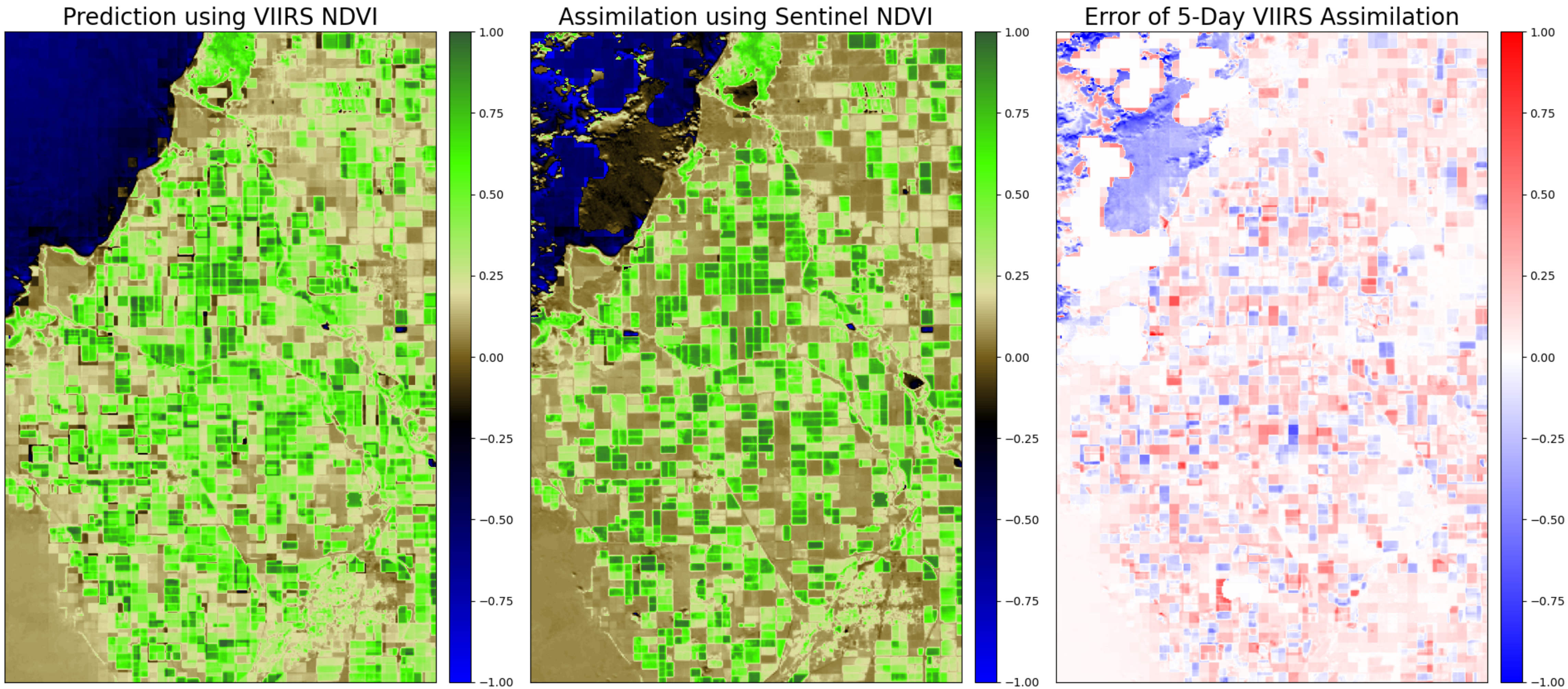

Comparison of error from 5-day VIIRS assimilation on July 14, 2020.

Discussion/Future Data Fusion Work

- Model parameterization
  - Balance influence of VIIRS on composite image after multiple days with no new Sentinel image
  - Parameterize for implementation on albedo
- Computational cost
  - Fusion of a 100km Sentinel-sized scene (~2.5 million pixels) takes between 10-30 min
- Incorporation of Landsat
- Evapotranspiration
  - Processing high-resolution estimates of NDVI and albedo with ECOSTRESS LST to estimate evapotranspiration

Updates on Other Proposal Objectives

Currently, ECOSTRESS ingests the (500m) GPP product from MODIS, which is combined with the (70m) ECOSTRESS L3 ET to produce the L4 WUE product.

1. **Objective 2: Improve the spatial resolution and accuracy of the L4 WUE product through incorporation of the BESS GPP algorithm**
   - Update: The team is currently working incorporating a new GPP algorithm, but do not have results to show as of yet.

ECOSTRESS data are provided as ISS ground-track swaths with separate files for geolocation, which requires cumbersome downloading and reprojection of very large files to produce useable rasters. On-the-fly analysis tools from the LP-DAAC, such as AppEEARS are severely hindered.

1. **Objective 3: Produce and deliver the new ECOSTRESS L2-4 data gridded in GeoTIFF, enabling AppEEARS and other tools for analysis.**
   - Update: All new data products will be directly produced as GeoTIFFs.

Acknowledgments

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