

Land Surface Albedo from a Constellation of Geostationary Satellites Compared and Fused with Polar-Orbiting Data

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Introduction

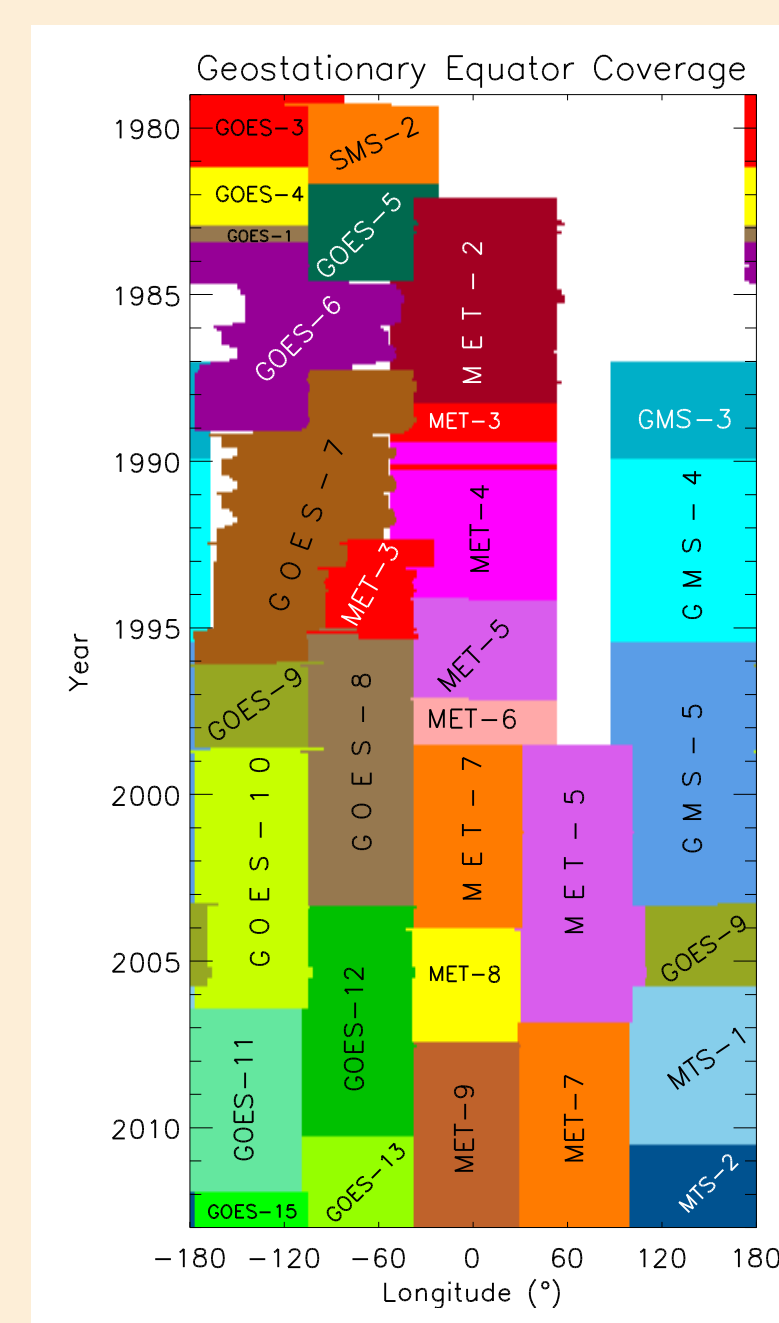


Sustained, Co-Ordinated Processing of Environmental Satellite Data for Climate Monitoring

- Aims to provide an international basis for the provision of high-quality long-term datasets of ECV's

- www.scope-cm.org

- One of 10 projects is the collaboration of EUMETSAT, JMA, and NOAA "Land surface albedo from geostationary satellites"



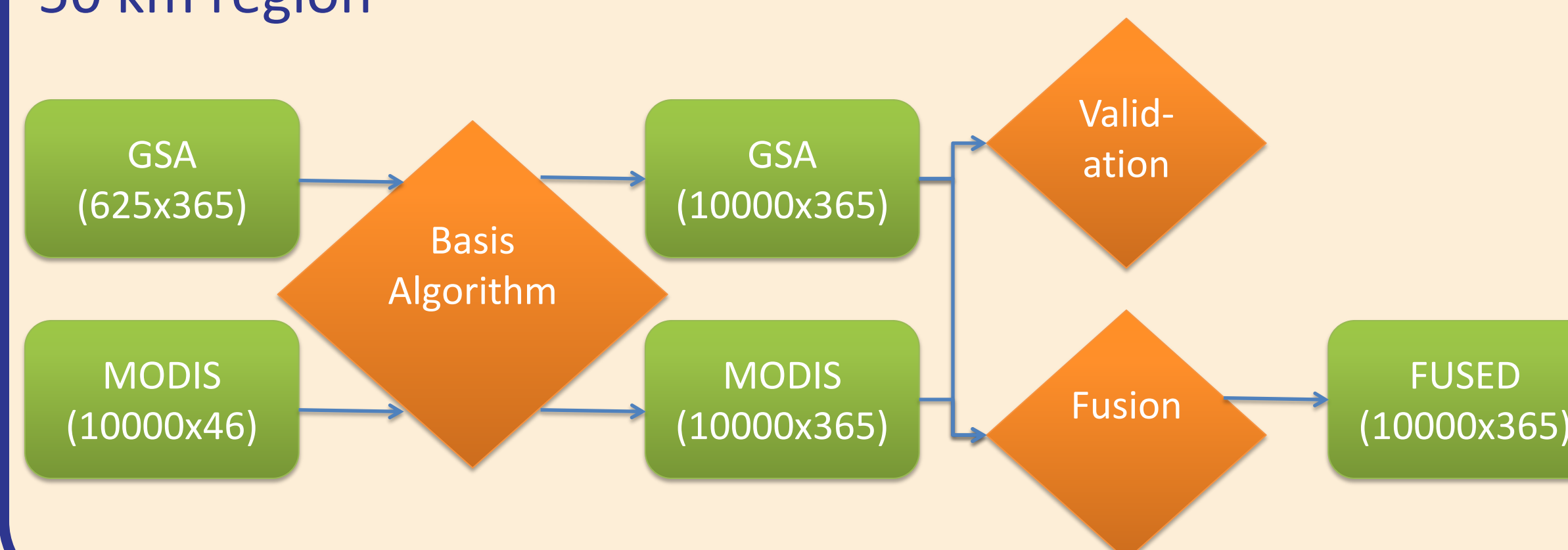
Geostationary constellation fields of view (above) and available time series (right).

Motivation

Spatial-Temporal Data Fusion Algorithm benefits:

- Provides a superior product leveraging the better temporal resolution of the geostationary product and the better spatial resolution of the polar-orbiting product
- Provides a framework for comparison of products on equal spatial and temporal footprints

Example of general flow for one year of data over a 50 km x 50 km region



Methodology

Consider two datasets: GSA ($j = 1$), MODIS ($j = 2$)

- Observations of type j represent spatial averages over spatial regions: B_{j1}, \dots, B_{jn_j} (i.e., $B_{1,1}, \dots, B_{1,625}$).
- Observations of type j represent temporal averages over days: A_{j1}, \dots, A_{jm_j} (i.e., $A_{1,1}, \dots, A_{1,365}$).
- Let Y_{jkl} be the observed value of data type j for region B_{jk} and day A_{jl} . Let $\mu(s, t)$ be the true albedo at spatial location s on day t .

$$E(Y_{jkl}) = \mu_{jkl} = \frac{1}{|A_{jl}| |B_{jk}|} \sum_{t \in A_{jl}} \int_{B_{jk}} \mu(s, t) ds$$

The true process is taken to be a linear combination of spatial and temporal basis functions:

$$\mu(s, t) = \sum_{u=1}^U \sum_{v=1}^V G_u(s) H_v(t) \theta_{uv}$$

This can be written in matrix form ($U = \#$ spatial basis functions, $V = \#$ temporal basis functions):

$$Y_j = \mu_j + \epsilon_j = \bar{G}_j \theta \bar{H}_j + \epsilon_j$$

$n_j \times m_j$ $n_j \times m_j$ $n_j \times m_j$ $n_j \times U$ $U \times V$ $V \times m_j$ $n_j \times m_j$

Theta is a matrix of spatial and temporal basis coefficients estimated via a penalized regression approach.

Results

As a pilot study we chose the 50 km x 50 km region surrounding the Niwot Ridge Ameriflux site in Colorado for the month of January 2003.

A thin plate spline spatial basis algorithm is utilized.

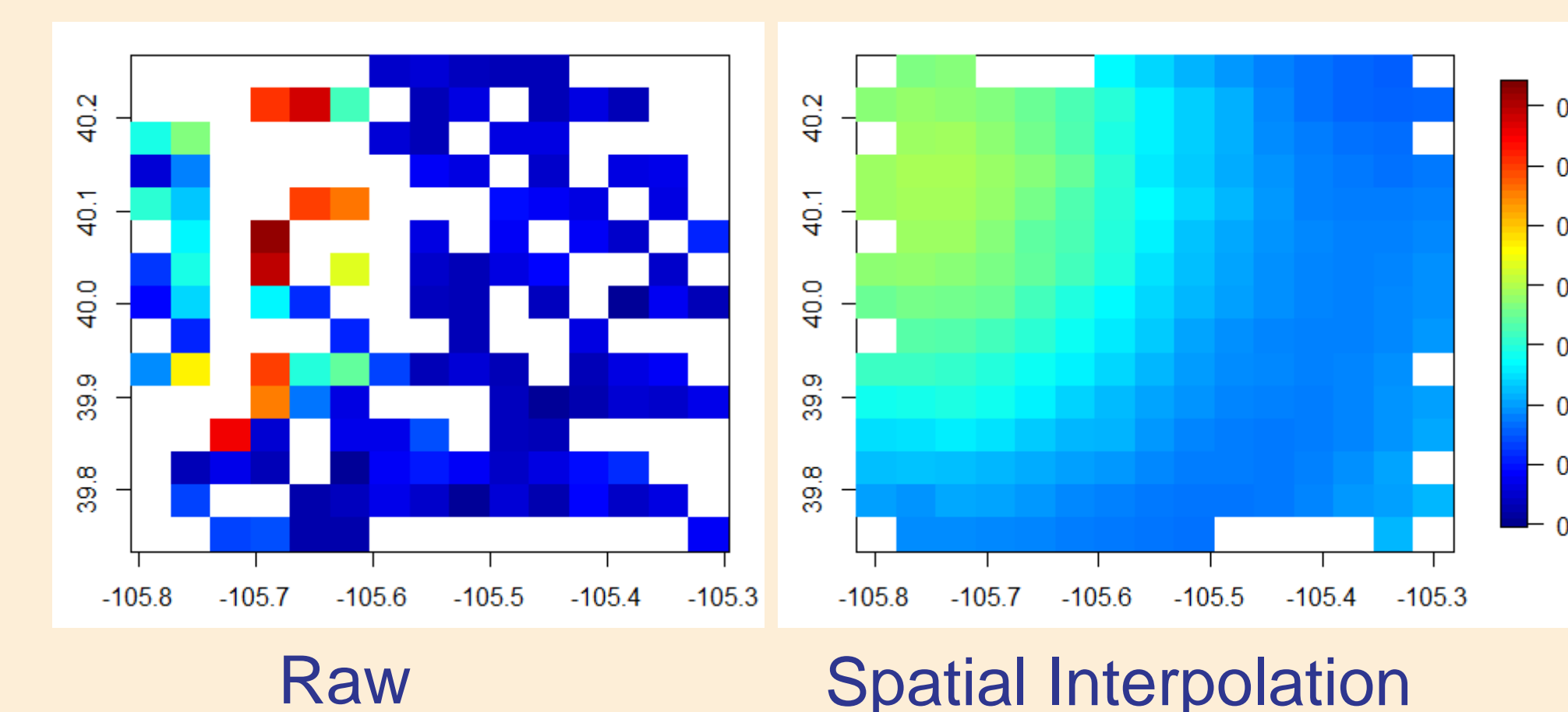
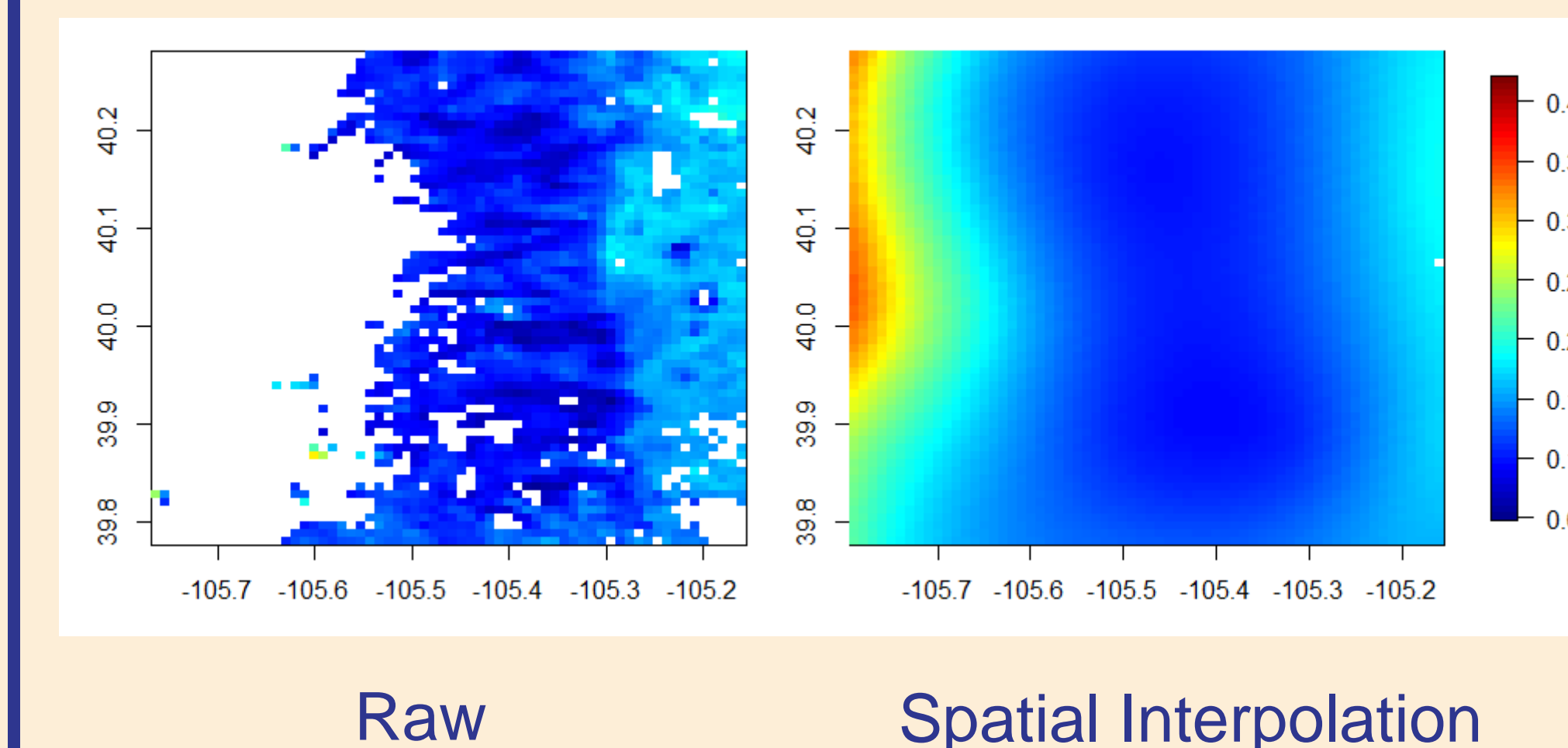
MODIS (MCD43A3):

- Jan 9, 2003 data (includes acquisition between days 9–24)
- 500-m spatial resolution
- Shortwave WSA
- Filtered for quality, using only full inversion data



GSA:

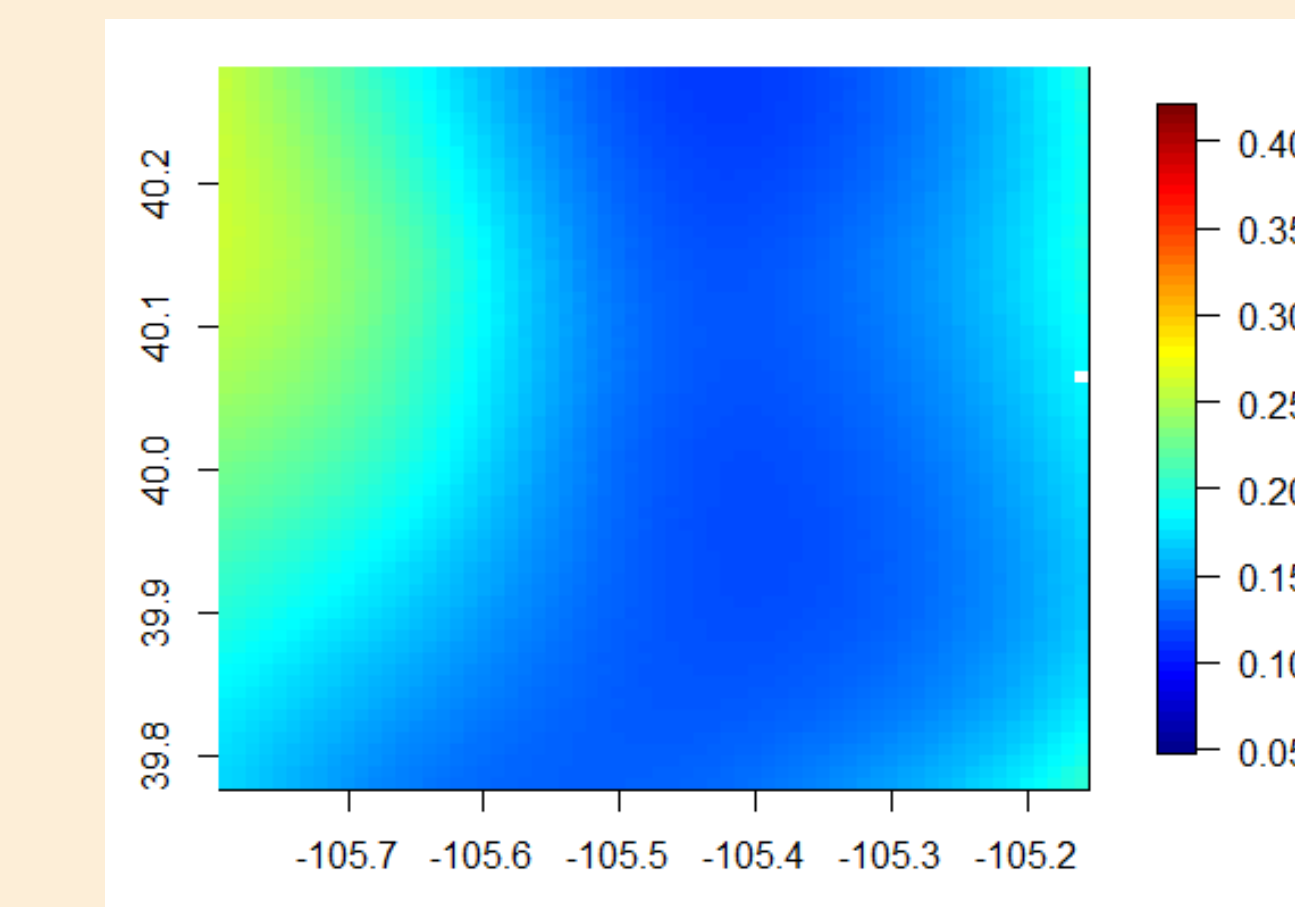
- Jan 9, 2003 data (daily)
- 2-km spatial resolution
- Shortwave WSA



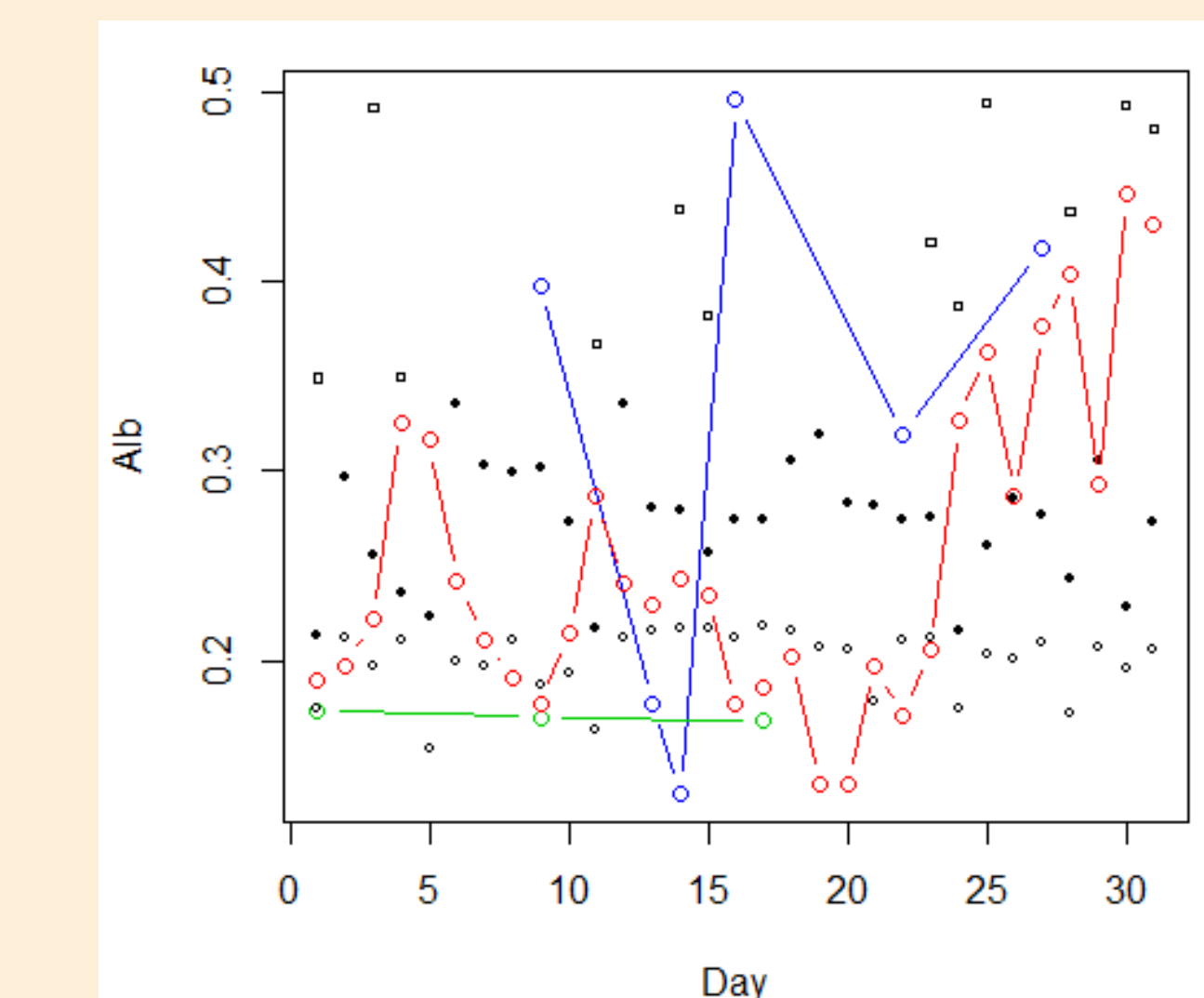
A temporal-distance weighting structure is used for the temporal basis functions.

Results

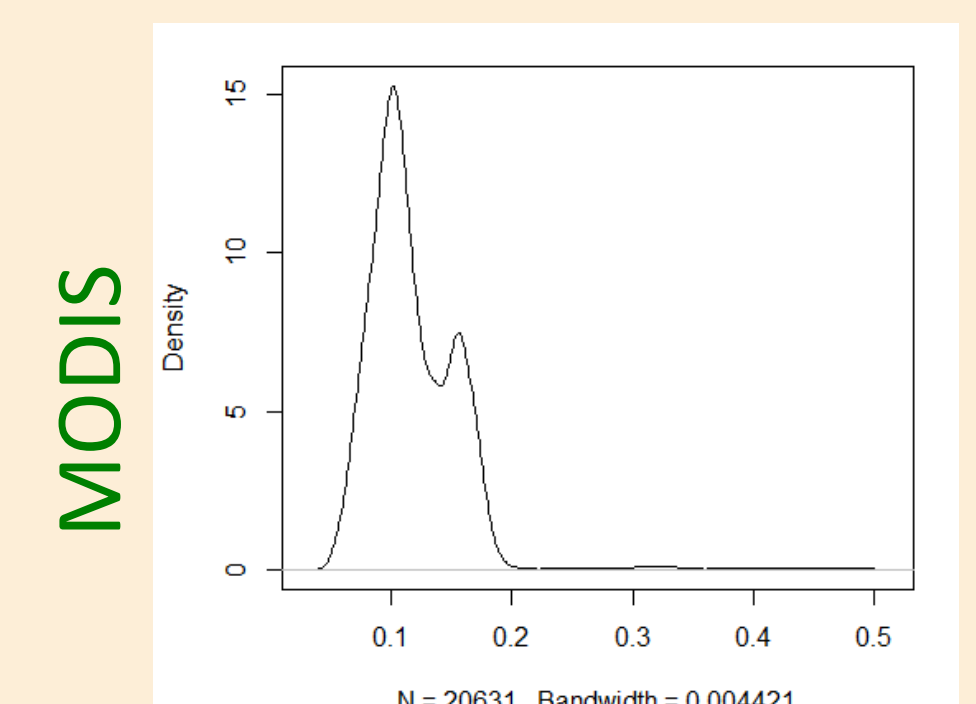
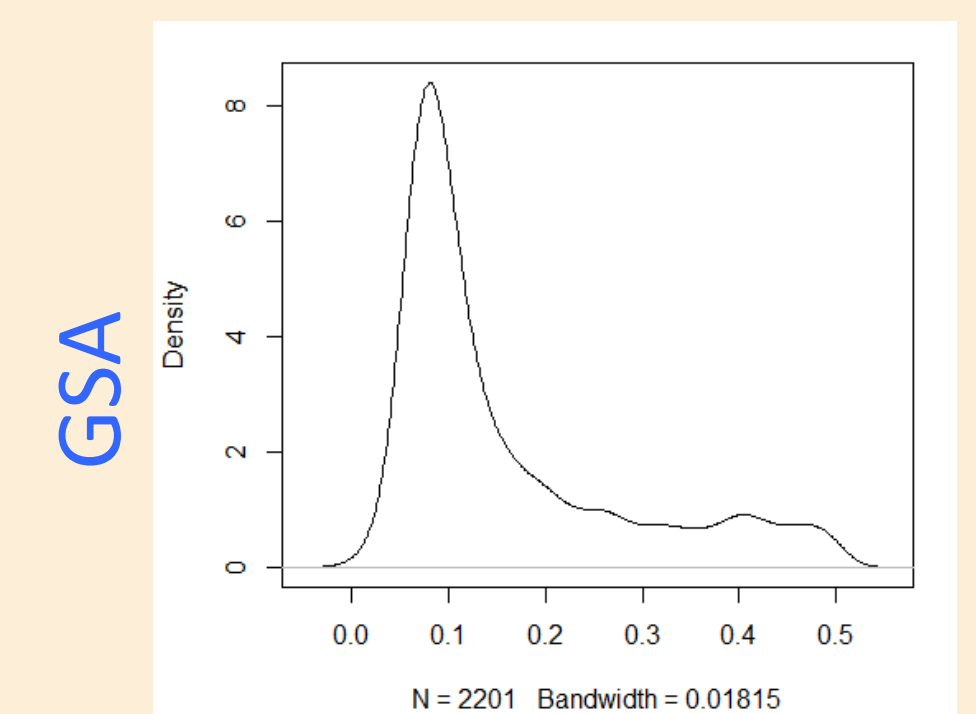
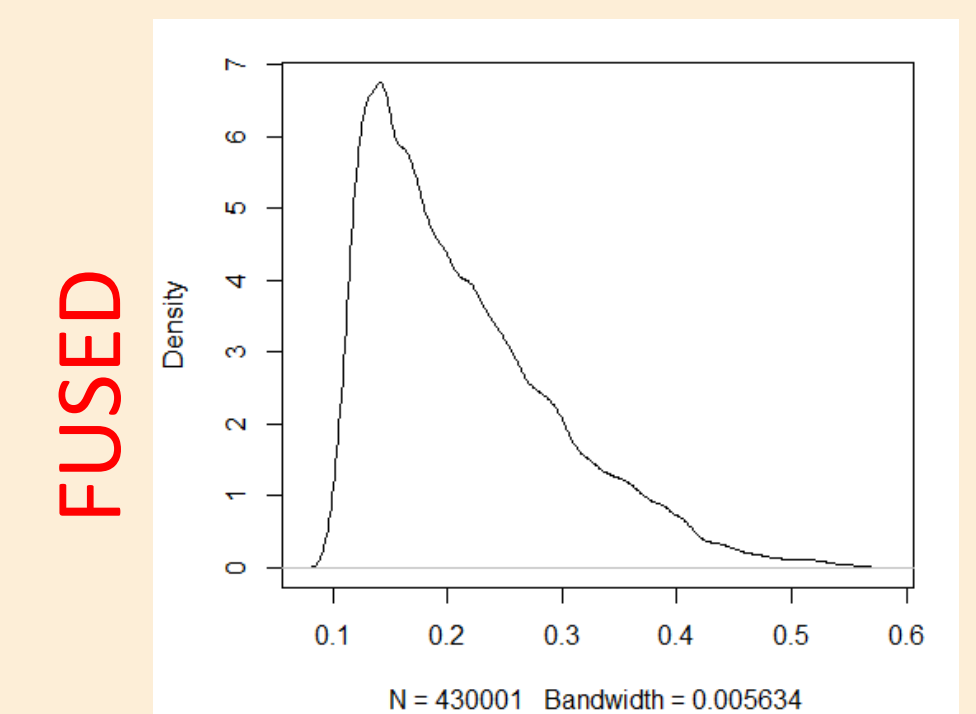
A fused product is produced at the spatial resolution of MODIS and the temporal resolution of GSA.



Jan 9, 2003 at 500 m



Jan 2003 tower data compared with MODIS, GSA, and FUSED.



Densities for Jan 2003 for entire region.

Summary

- Fused product demonstrates the ability to leverage the spatial resolution advantages of the polar-orbiting-based product with the temporal resolution advantages of the geostationary-based product
- Fused product fills spatial and temporal gaps of missing data in either dataset
- The choice of basis function complexity balances computational efficiency with smoothing effects
- Validation can be performed with in situ measurements