

Improving fractional snow-covered area estimations through increased spatial fidelity



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SPIReS

Snow Property Inversion from Remote Sensing (SPIReS) [1] estimates fractional snow-covered area (fSCA) from surface reflectance observations. To estimate the fSCA from a single surface reflectance observation \mathbf{R} of a given location, SPIReS requires a snow-free reference surface reflectance observation \mathbf{R}_0 of the same location.

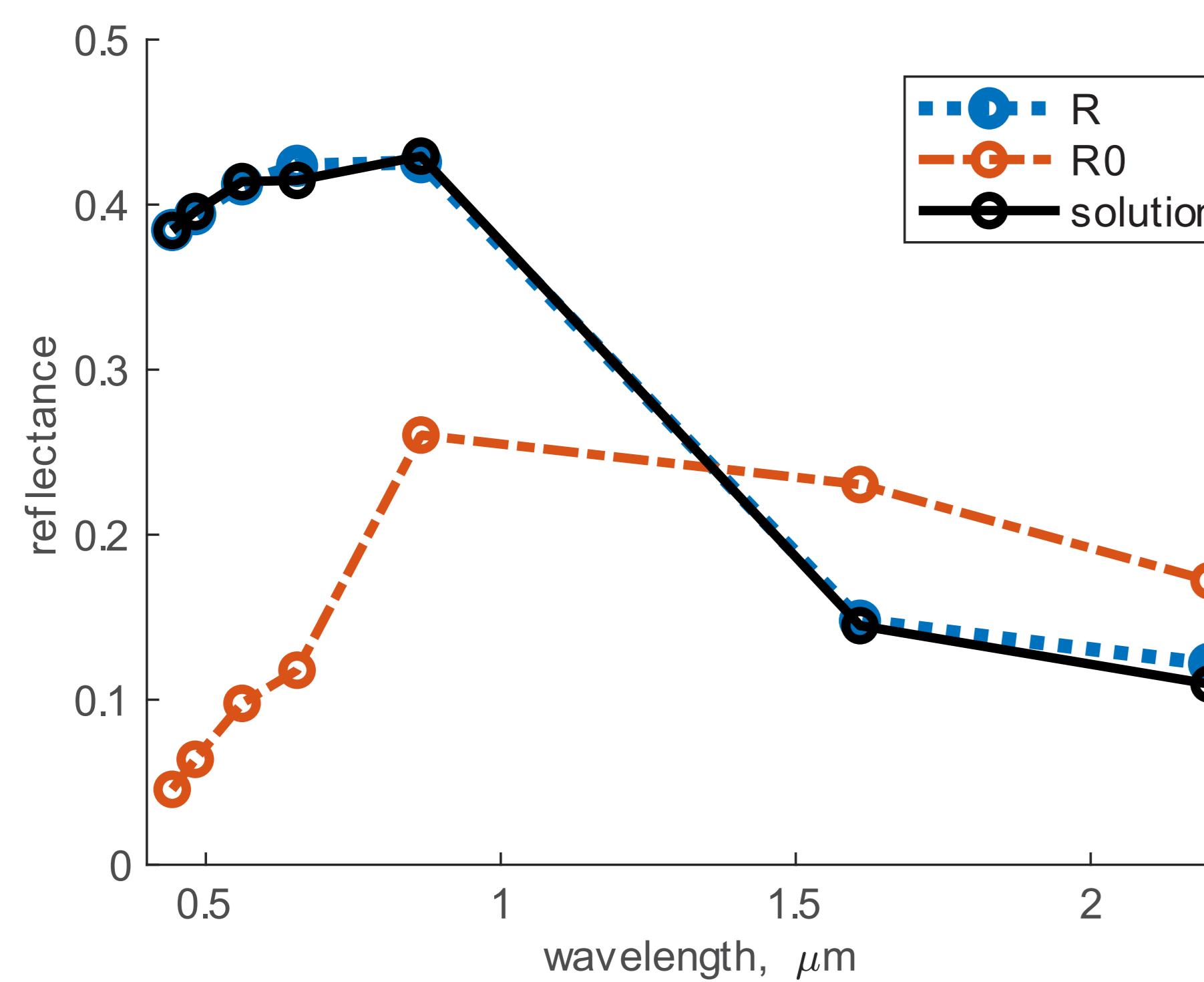


Figure: Figure 2 of [1]. Spectrum \mathbf{R} observed under fractionally snow-covered conditions. Reference spectrum \mathbf{R}_0 observed under snow-free conditions. SPIReS solved for the solution while estimating fSCA, fractional shade, snow grain size and Light absorbing particle concentration.

Spatial mismatching

The MODIS geolocation accuracy is approximately 50 m at nadir [4], whereas data is gridded into 500 m cells for level 3 (L3) products. The discretization causes a loss of spatial precision, leading to spatial mismatching of \mathbf{R} and \mathbf{R}_0 that propagates errors into the SPIReS' fSCA estimations.

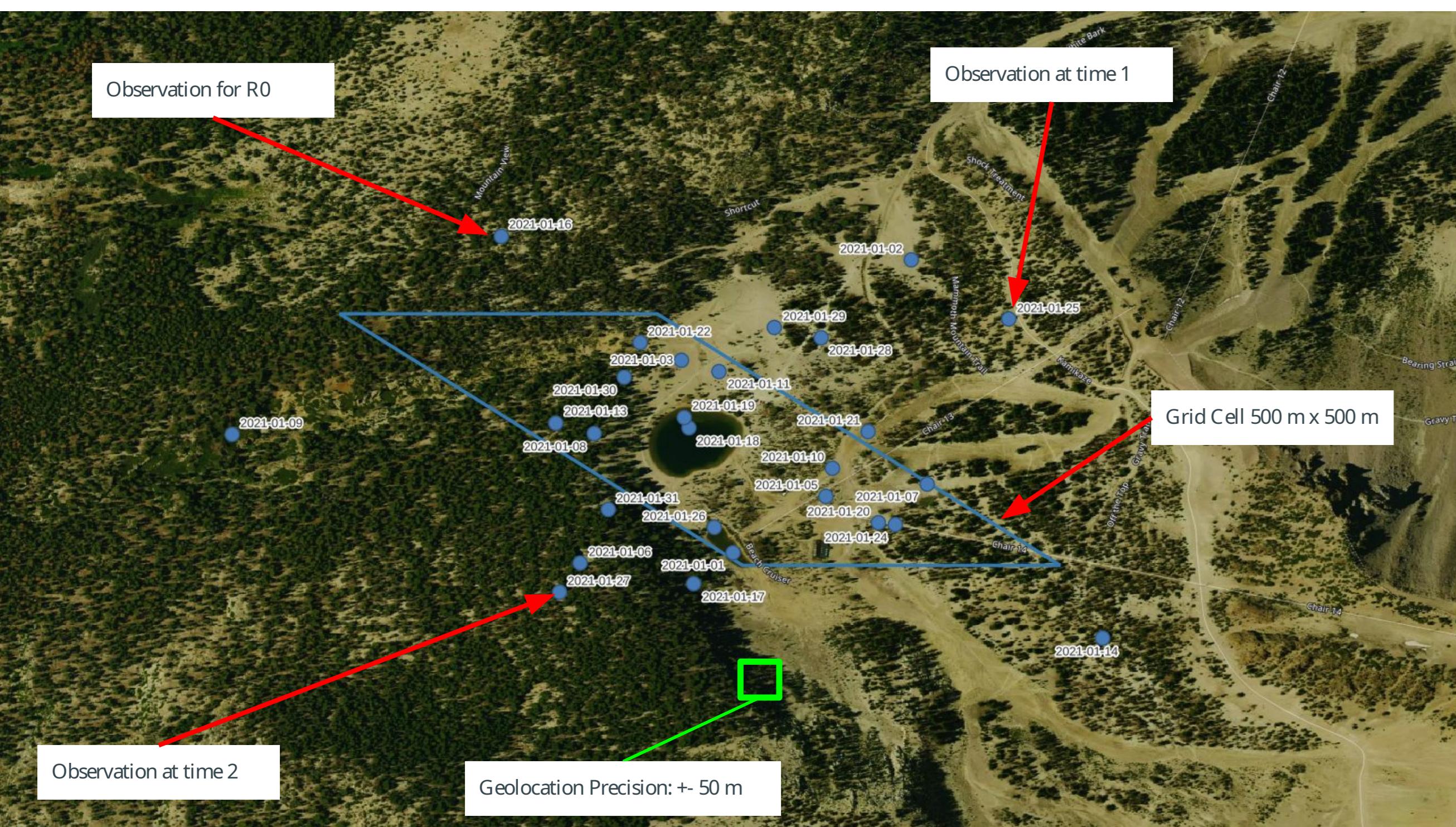


Figure: Geolocation of MOD09 observations at 500 m resolution associated with a single MODIS grid cell in the Region of Mammoth Lakes for one month.

Further, when evaluating the accuracy of the estimations, we tend to compare the estimates with ground truth data spatially coinciding with grid cells. Since in reality, the observation's footprint differ from the footprint of the cell, an error is introduced into the accuracy evaluation.

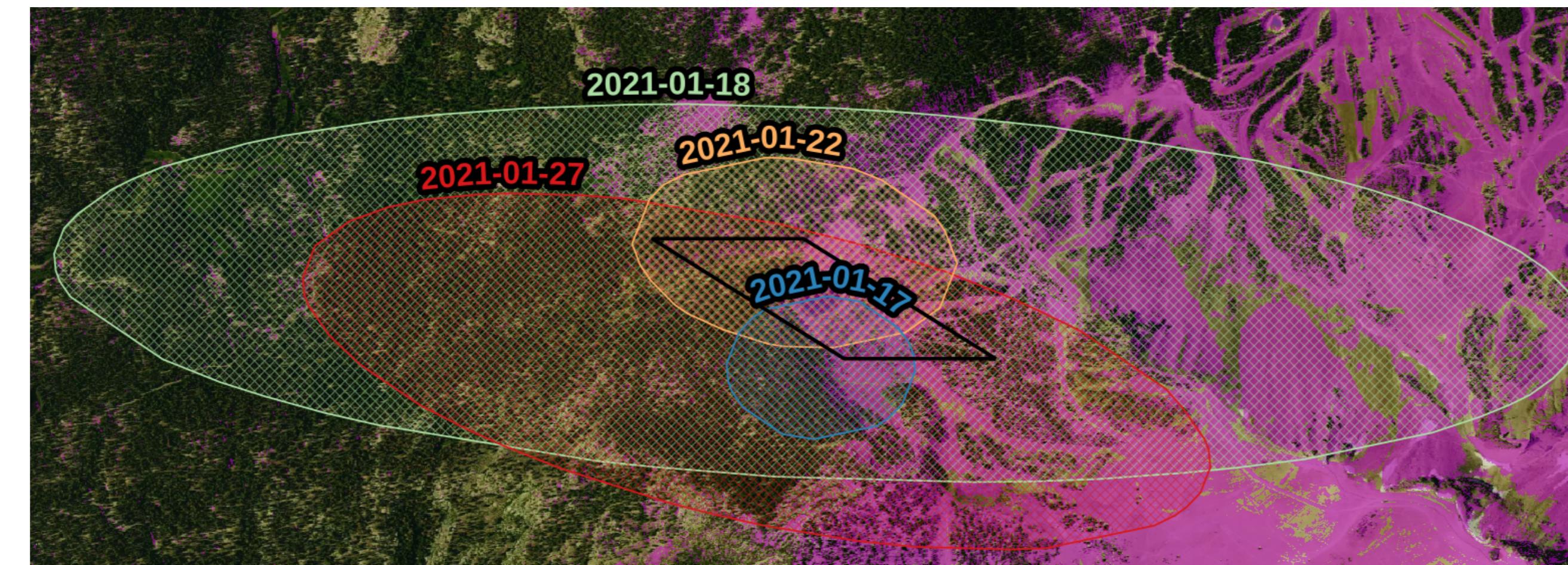


Figure: iFOV footprint approximation based on the viewing zenith and azimuth for observations associated with the same grid cell (black). Magenta: ground-truth data used to evaluate the accuracy of the fSCA estimates.

The spatial mismatching of \mathbf{R} and \mathbf{R}_0 and the wandering observation footprints associated with a single cell may partially explain the high fluctuations in the fSCA estimates for a 'fixed' location (a grid cell) over time.

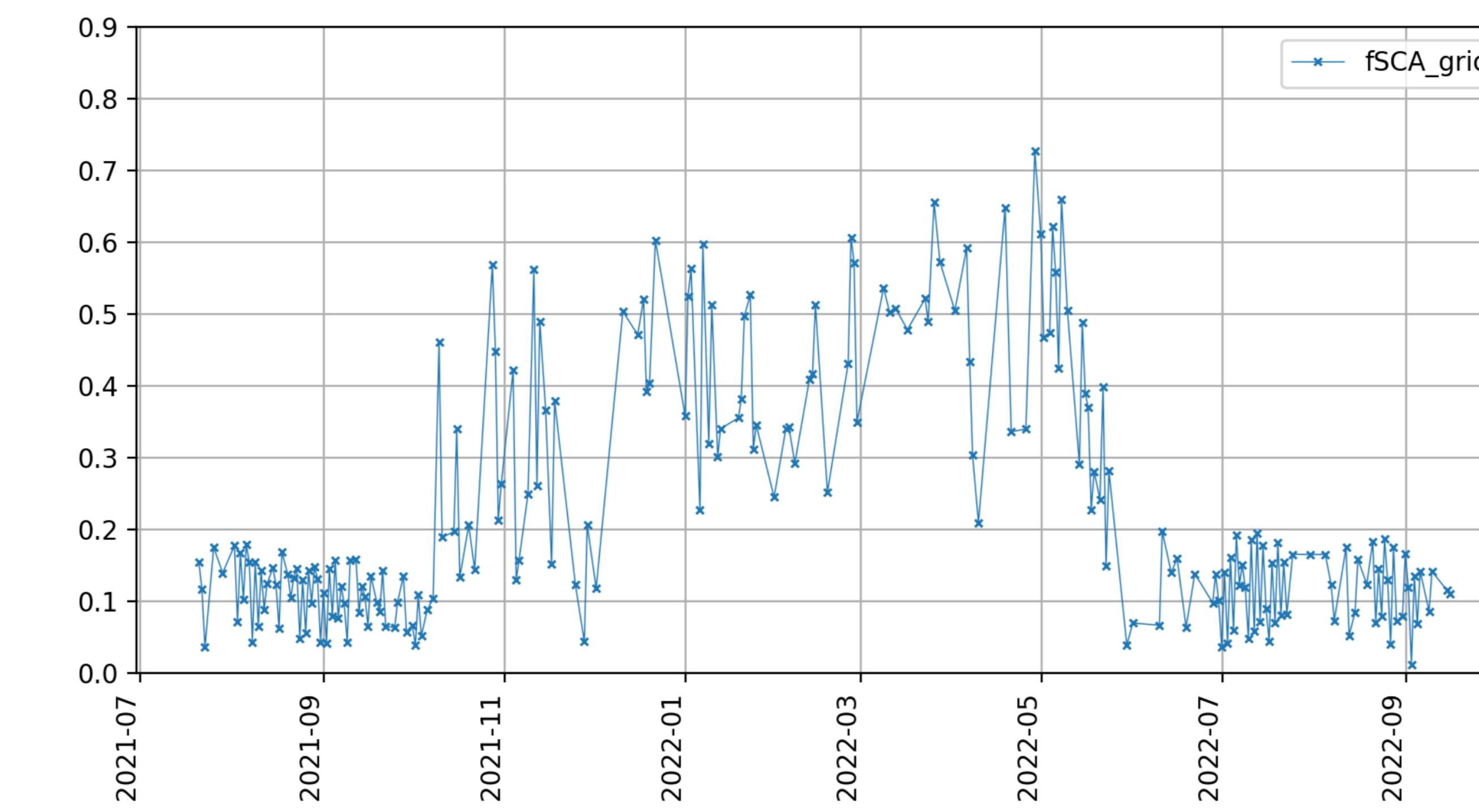


Figure: Timeseries of fSCA calculated for a single grid cell. Note the fSCA estimate fluctuations and values well above 10% during the (snow-free) summer.

Improving spatial fidelity

To forgoe the inaccuracies introduced through the gridded data, we indexed ungridded level 2 (L2) data with the *Spatiotemporal Adaptive Resolution Encoding* (STARE) [2], a global universal geolocation encoding and used the indexed observations as inputs for SPIReS. Using the STARE indexed data we can:

- ▶ find closer matches between \mathbf{R} and \mathbf{R}_0 by freely adjusting the spatial resolution at which observations are matched.
- ▶ improve the algorithm accuracy evaluation by finding ground truth data that more closely coincides with the footprint of the observation.

We further considered the viewing geometry to find \mathbf{R}_0 s that were made under similar viewing conditions as \mathbf{R} . This is relevant in mountains where opposing mountain faces may have differing constituent endmembers.

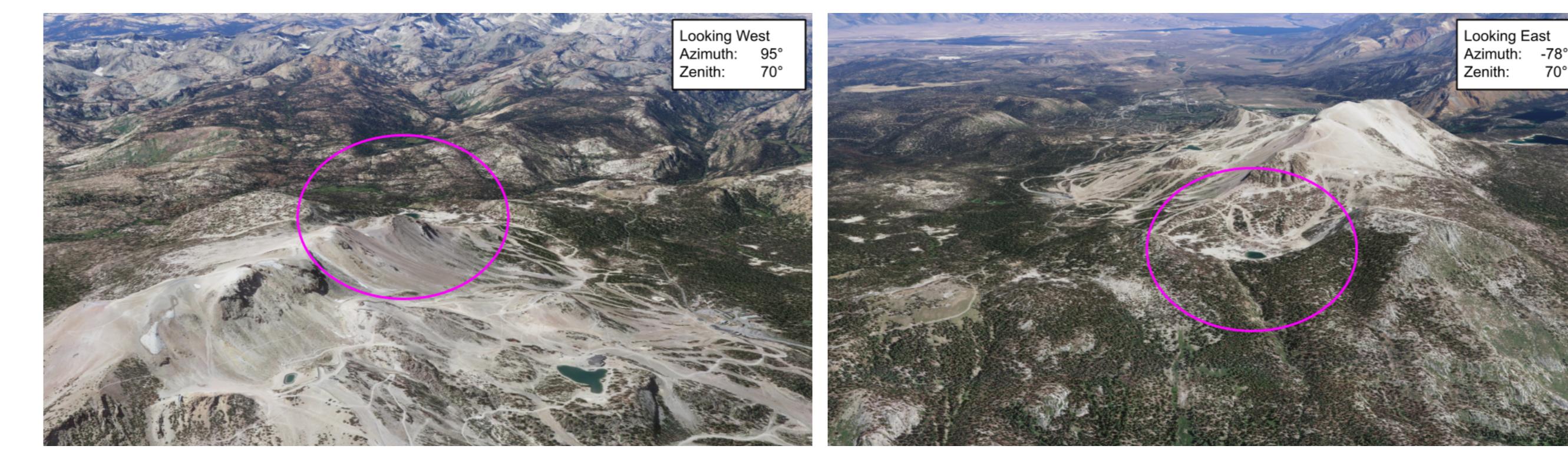


Figure: View onto the same location (Reds Lake) from a MODIS overpass east (left) and west (right). More vegetation is visible when looking west.

Results

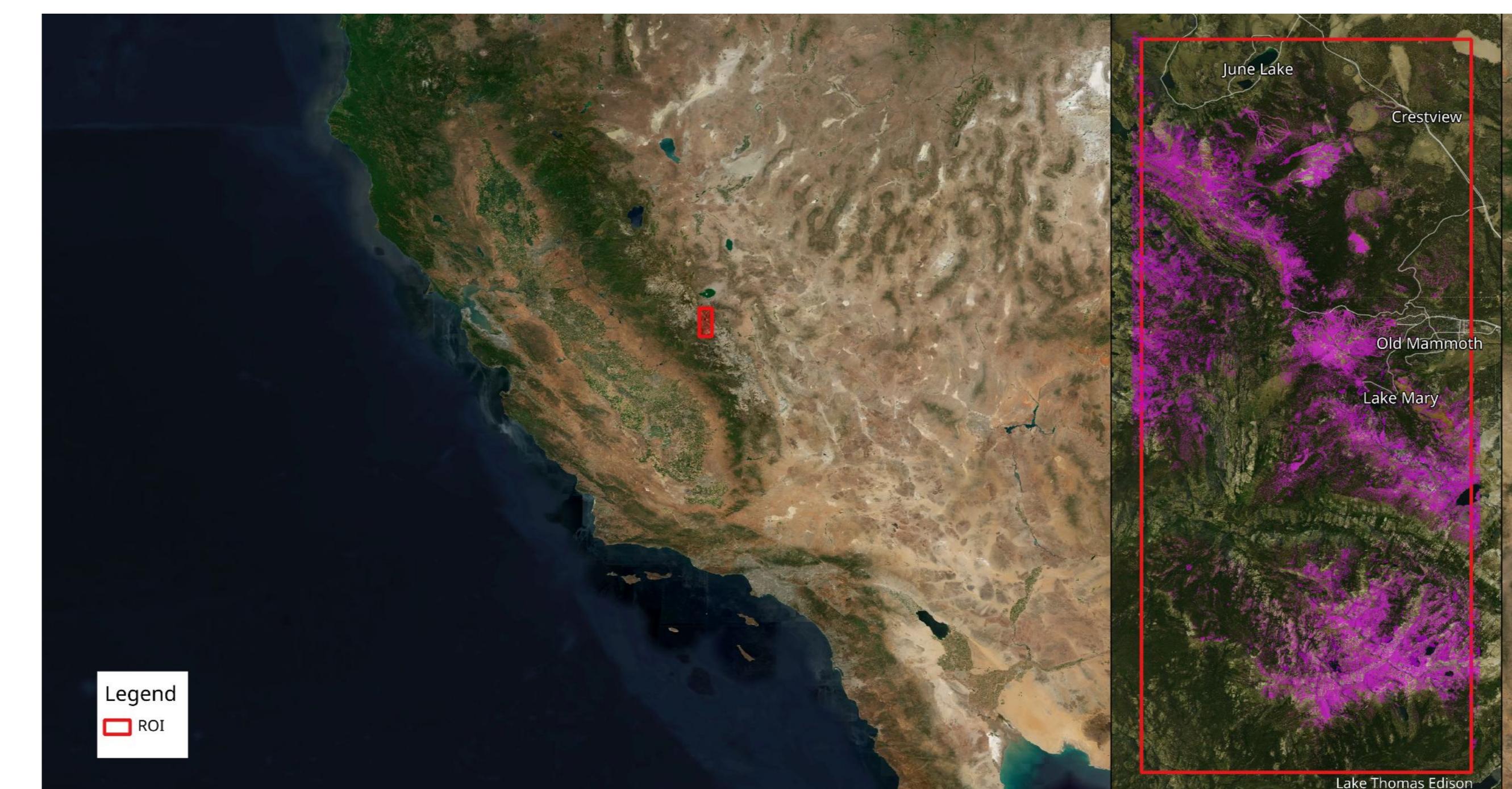


Figure: Region of interest (ROI) in the eastern Sierra Nevada.

Over our ROI and the timespan between 2017-12-05 and 2017-12-15, during which no notable ablation nor melt occurred, we computed the fSCA estimations of SPIReS from gridded L2 data and from STARE indexed L3 data. We compared those estimates against high resolution snowmaps [3] to evaluate the accuracy.

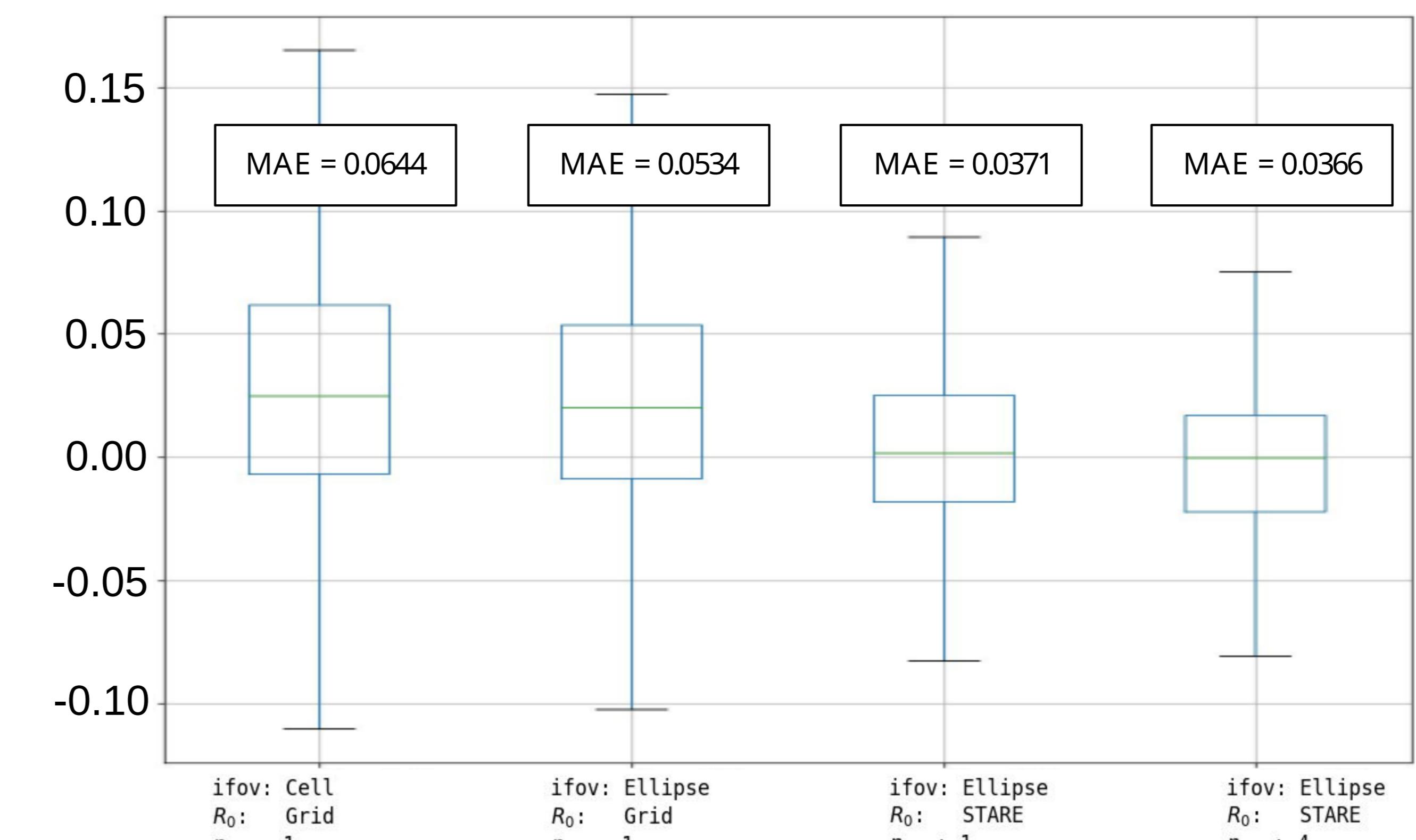


Figure: Mean Absolute Error (MAE) from left 1) Using cells as iFOV approximations and grid to find $\mathbf{R} / \mathbf{R}_0$ matches. 2) Using ellipses as iFOV approximation. 3) using STARE to find $\mathbf{R} / \mathbf{R}_0$ matches. 4) considering the viewing angles.

The STARE approach allows us to compute fSCA timeseries for arbitrary regions and from multiple sensors, resulting in more credible timeseries than for cells.

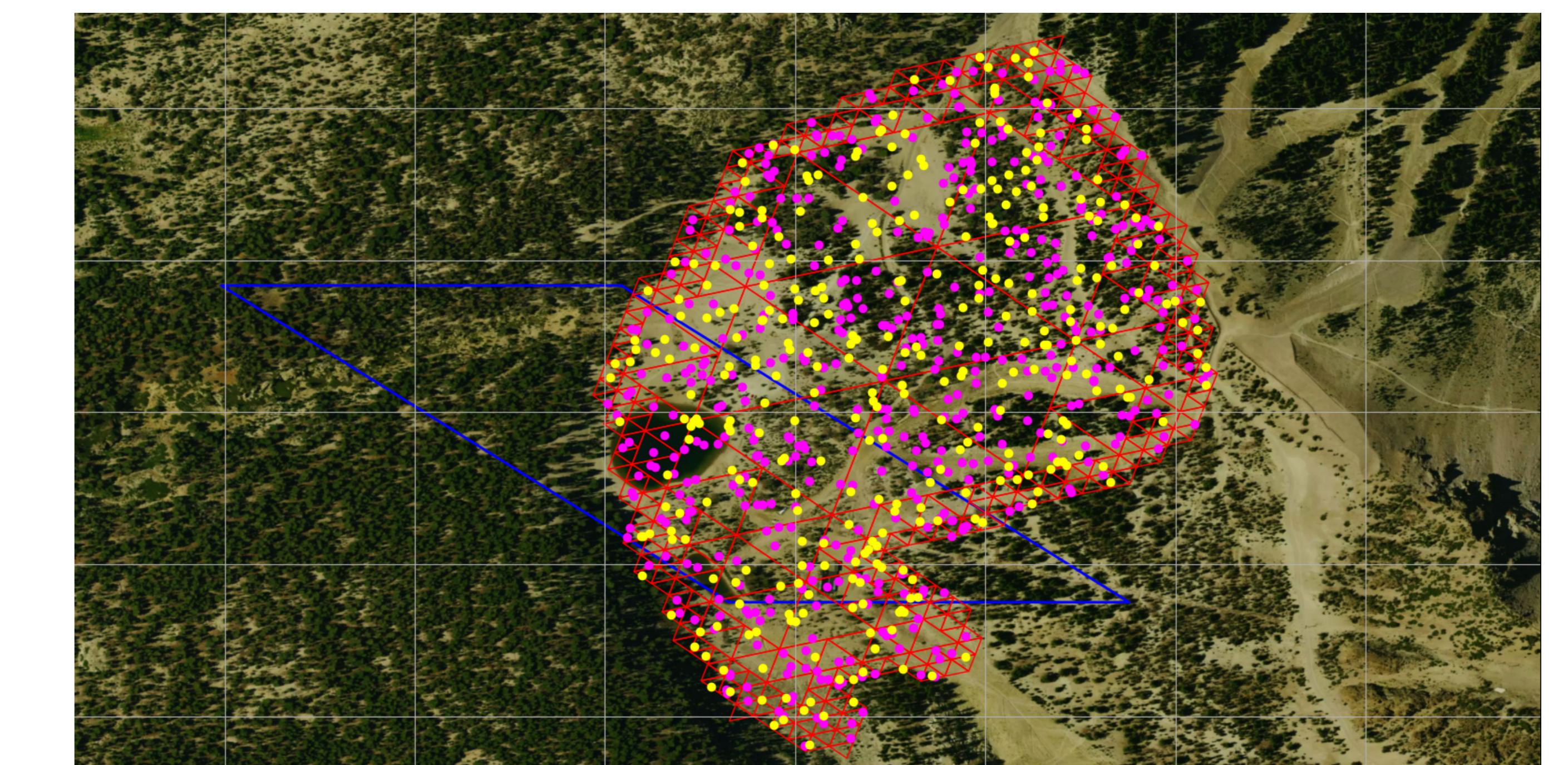


Figure: Geolocations of MODIS terra (magenta) and VIIRS suomi (yellow) surface reflectance observations associated with a complex region.

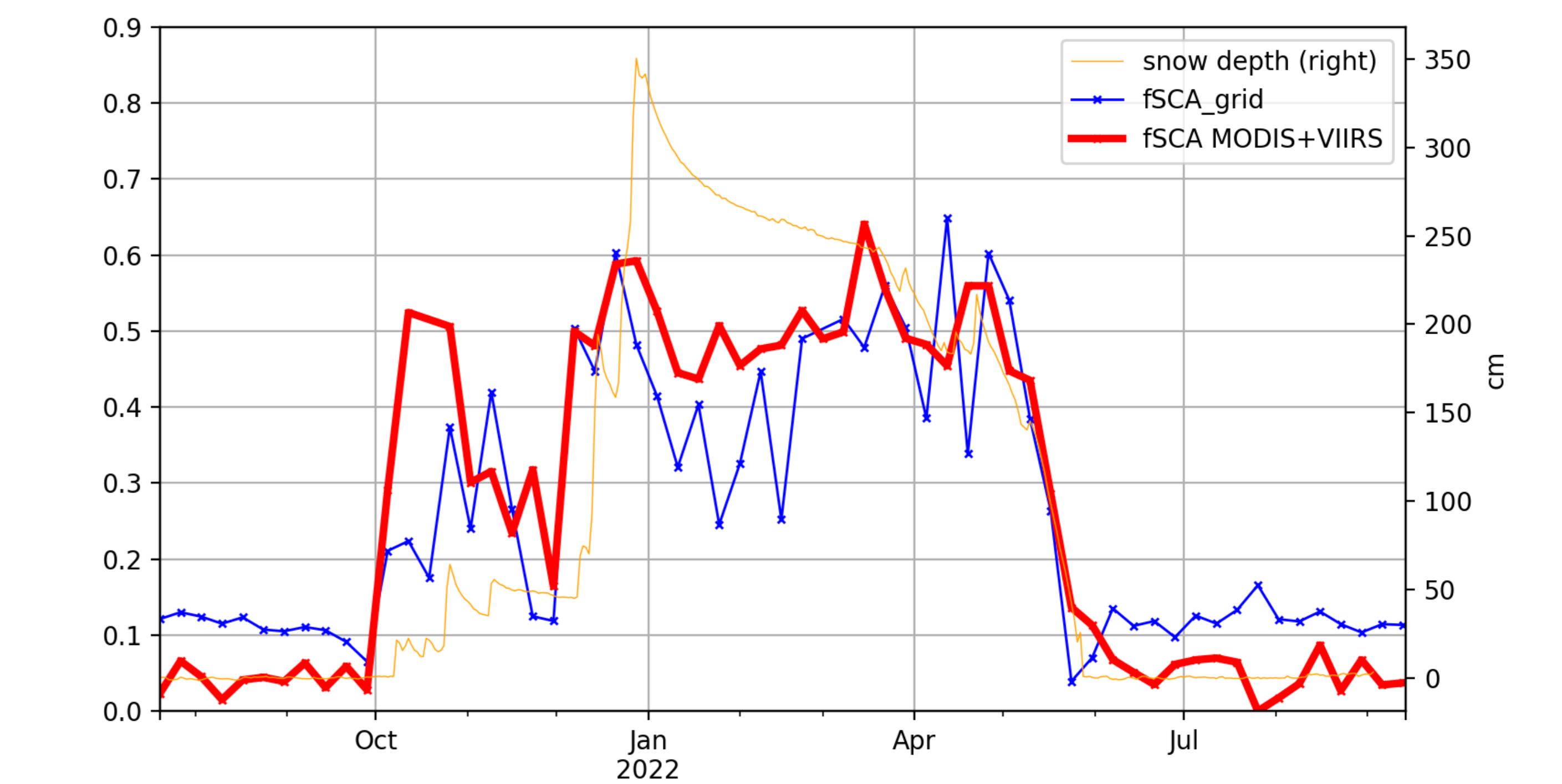


Figure: fSCA timeline for a complex region for combined MODIS and VIIRS observation (red) and an adjacent grid cell (blue). Both resampled to 7 days.

References

- [1] Edward H. Bair, Timbo Stillinger, and Jeff Dozier. "Snow Property Inversion From Remote Sensing (SPIReS): A Generalized Multispectral Unmixing Approach". 2021.
- [2] Michael L. Rilee et al. "STARE into the future of GeoData integrative analysis". 2021
- [3] Timbo Stillinger and Ned Bair. Viewable Snow Covered Area Validation Masks over Rugged and Forested Terrain. 2020
- [4] Robert E. Wolfe et al. "Achieving sub-pixel geolocation accuracy in support of MODIS land science." 2002.

Acknowledgments

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