FluoMap: Retrieving Sun-induced fluorescence from space using machine learning

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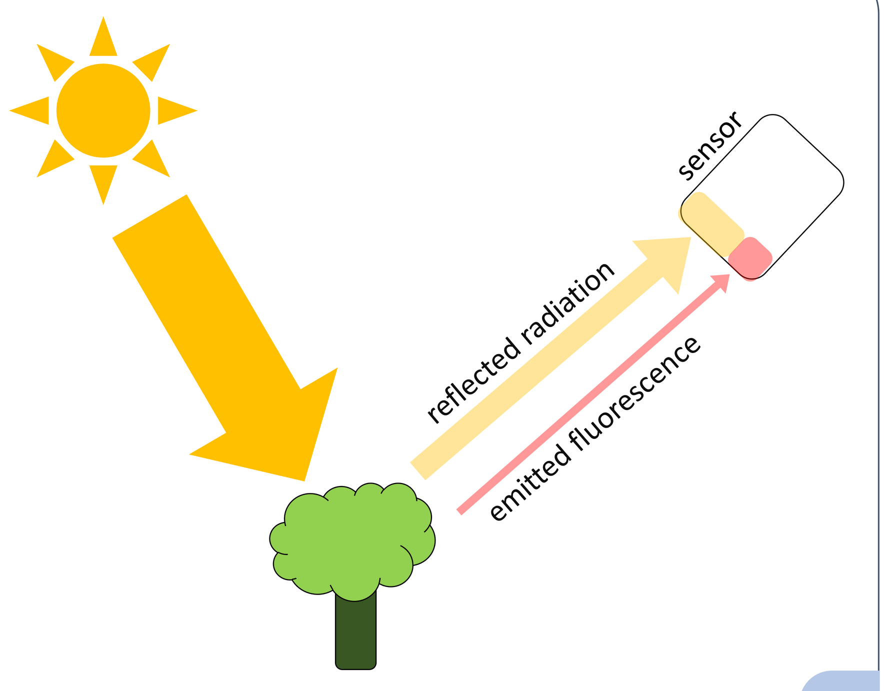
Introduction

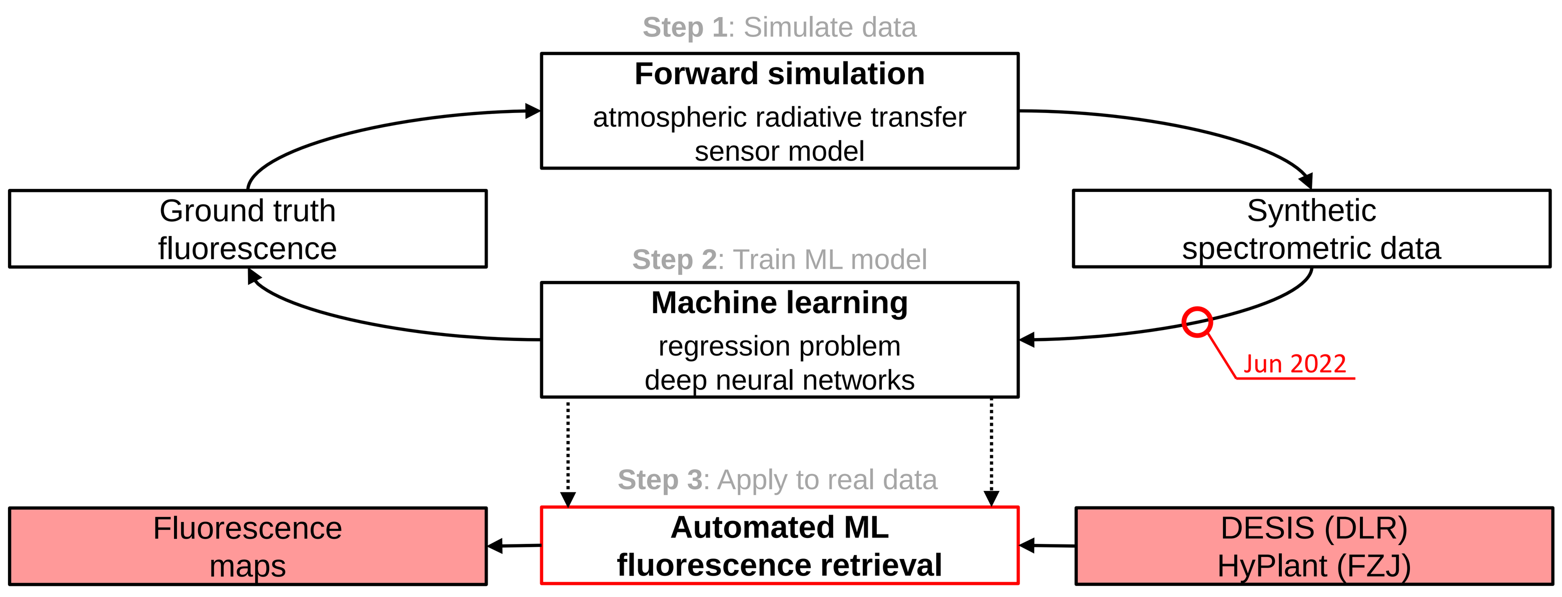
Plants routinely harvest energy from Sun light through photosynthesis, re-emitting light in the process at red and infrared wavelengths. This re-emission, dubbed Sun-induced fluorescence (SIF), carries information on the efficiency of photosynthesis and it provides a window into the health status of plants. Despite decades of progress [1,2], the measurement and monitoring of SIF from space remains challenging at best to this day. This is mainly due to the smallness of the fluorescence signal on the ground, the effect of the atmosphere on the signal on its way to the instrument, and the need to operate a stable, very high spectral resolution instrument in space.



Project description

FluoMap | Helmholtz AI | DLR | FZJ | 2020–2023

The Helmholtz AI-funded project FluoMap is a joint collaboration between DLR and FZJ and aims at tackling the space-based retrieval of fluorescence with machine learning (ML) algorithms. The ML approach is particularly appropriate for this high-dimensionality regression problem due to the small magnitude of the signal, high noise levels and numerous unknown variables, all characteristics that prevent the use of classical inversion techniques.

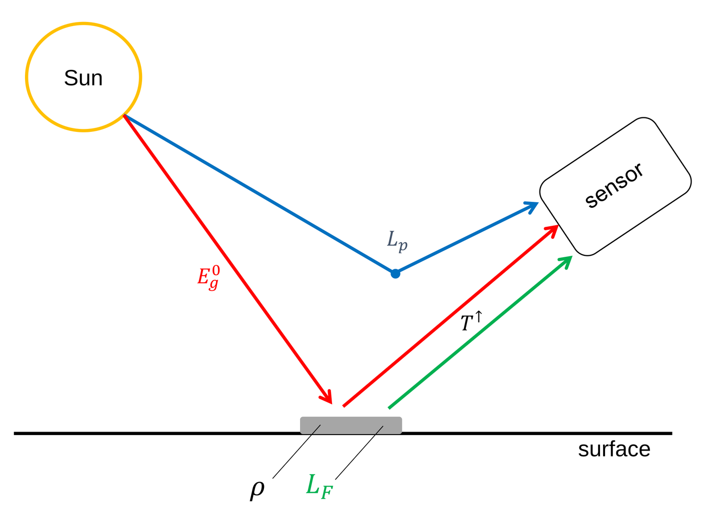


Simulation of DESIS and HyPlant spectrometer data

Step 1

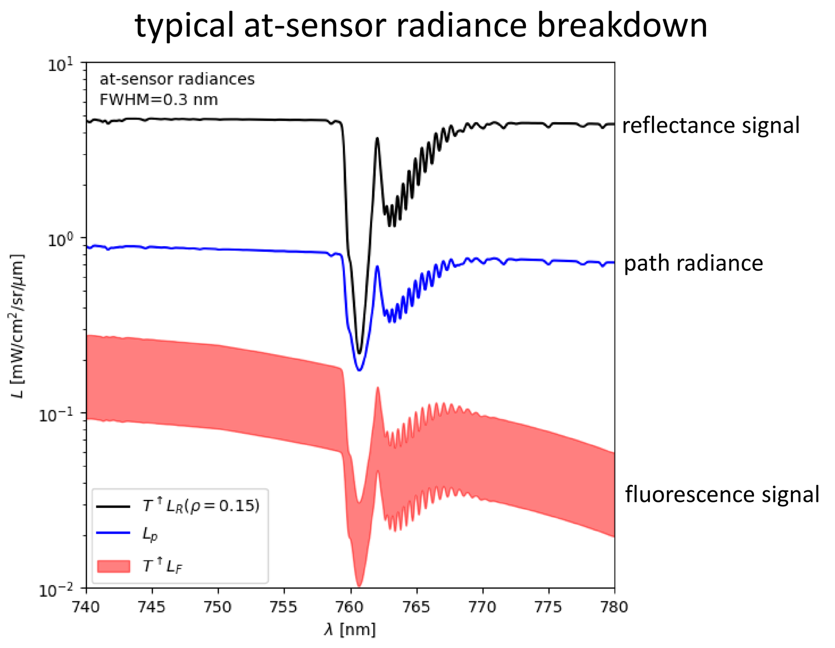
A forward simulator has been designed and implemented to simulate DESIS- and HyPlant-like spectra at the O2A absorption band (around 761 nm) given a set of atmospheric, geometric, target and sensor data. The simulator uses MODTRAN6 [3] to treat the propagation of the signal through the atmosphere and the intimate knowledge of the DESIS and HyPlant instruments present in the team to accurately simulate sensor uncertainties. The body of simulated data constitutes a building block for the supervised learning and error estimates to be performed by ML models.

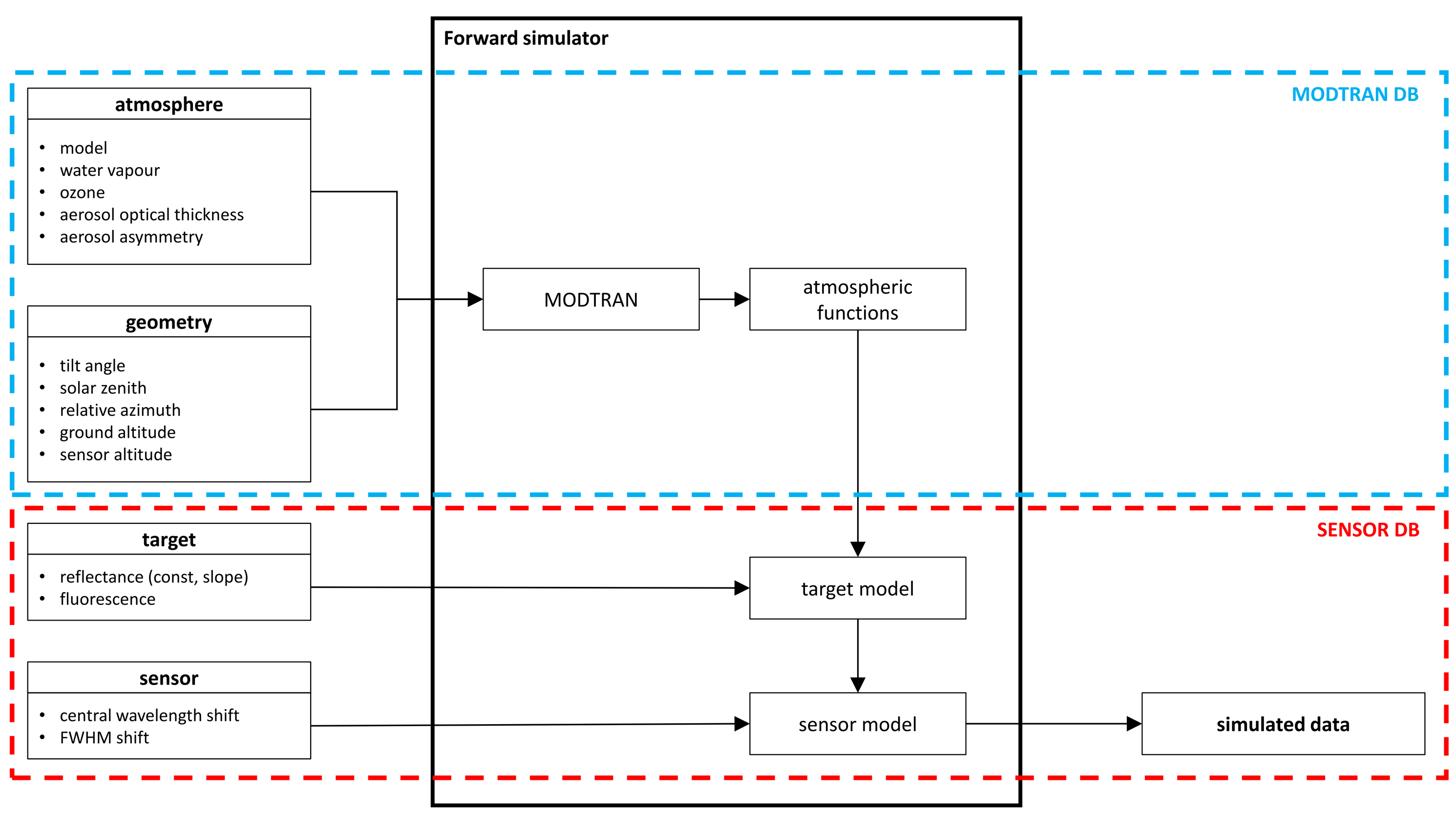
radiative transfer through atmosphere



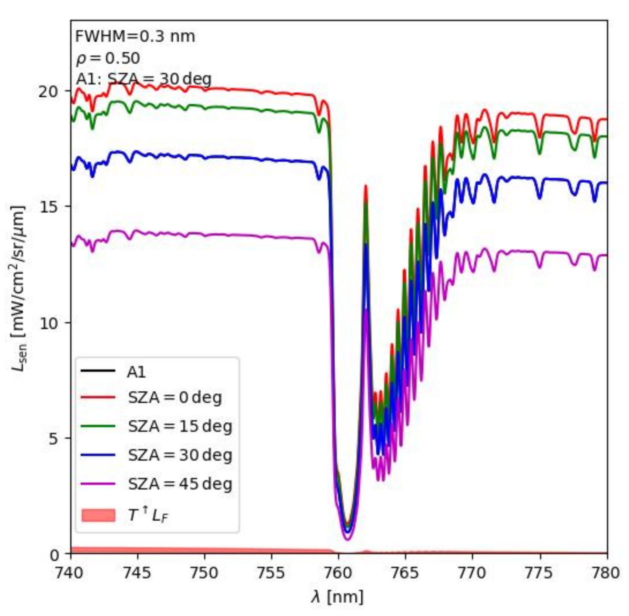
$$L_{\text{sen}} = L_p + \frac{T^\uparrow E_g^0 \rho}{\pi(1-\rho S)} + T^\uparrow L_F$$

typical at-sensor radiance breakdown





example output of forward simulator



databases of simulated data

Instrument	Specification	Databases			
		DB #1	DB #2	DB #3	DB #4
DESIS	Input dimensions	3	5	9	11
	Output dimensions	13	13	13	13
	Number of samples	4.6×10^4	2.4×10^6	4.2×10^6	1.2×10^7
	Data size [GB]	0.02	1.1	1.9	5.8
HyPlant	Input dimensions	3	6	11	13
	Output dimensions	349	349	349	349
	Number of samples	4.6×10^4	2.4×10^6	4.4×10^6	1.5×10^7
	Data size [GB]	0.2	10.3	18.7	65.8

The databases were generated with different sampling methods (uniform, random, Halton) for uniformity and with increasing complexity to help the learning process.

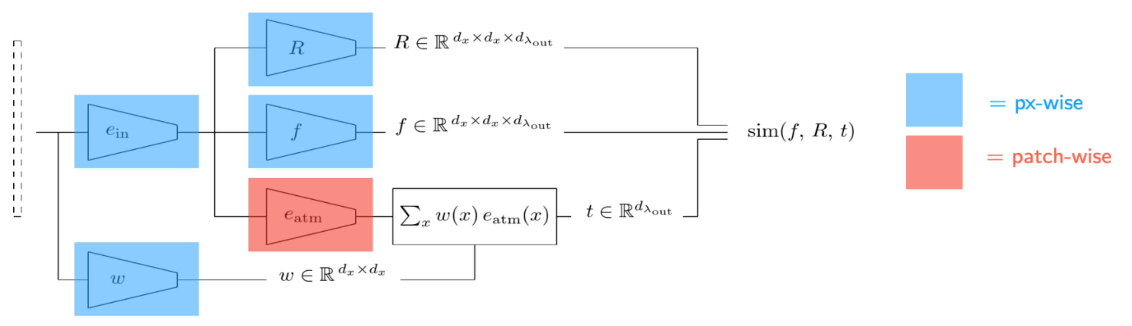
Learning with HyPlant data: self-supervised SIF retrieval

Step 2

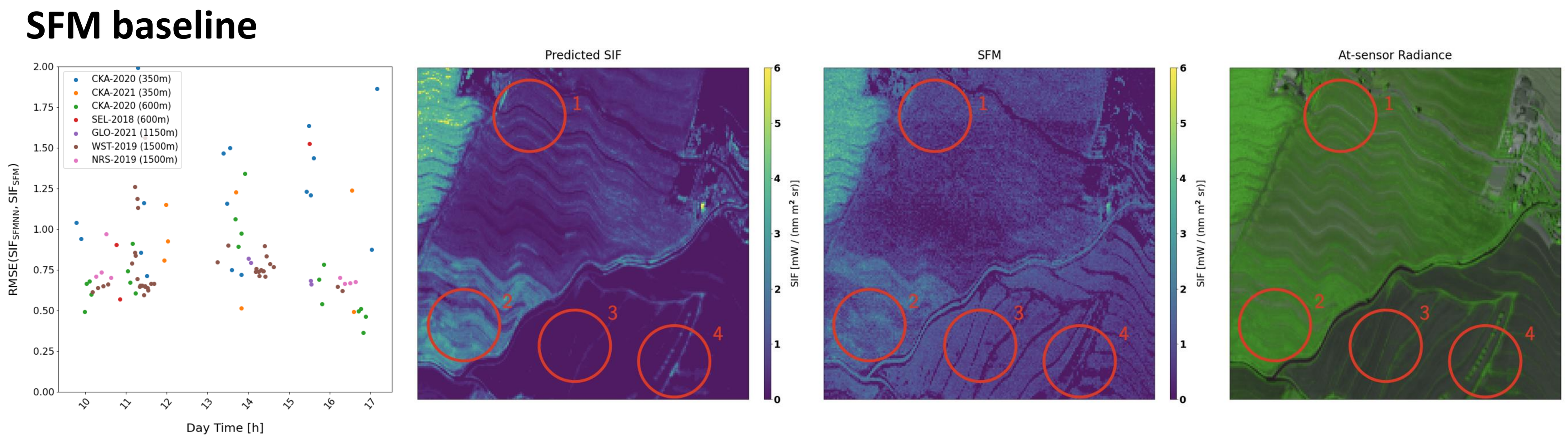
A first ML model for SIF retrieval has been implemented based on existing HyPlant data available at FZJ. This effort has been guided by the fluorescence retrieved by traditional methods such as the spectral fitting method (SFM) [4], as well as self-supervised learning, and it is the starting point for the later phases of the project. Although still preliminary, the results of this ML model are promising.

$$L^{\text{at-sensor}} = t_\uparrow\left(t_\downarrow(E_s^0,\theta_s)\cdot R + f_{\text{TOC}}\right) \approx \boxed{t_\uparrow t_\downarrow E_s^0 \cos(\theta_s)\cdot R} + \boxed{t_\uparrow f_{\text{TOC}}}$$

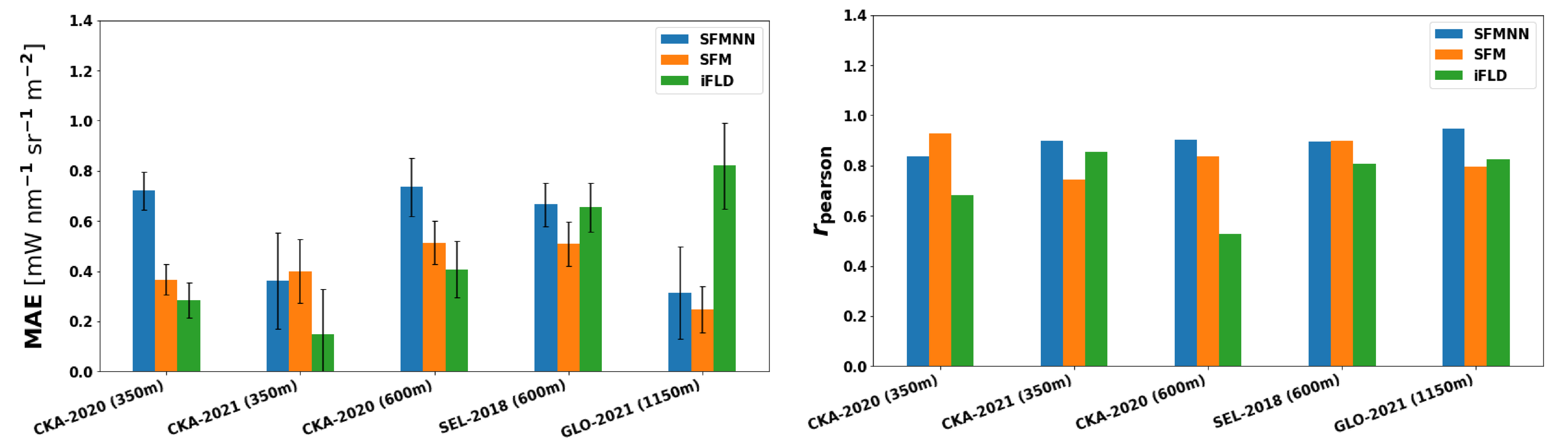
$$\ell(y,\hat{y}) = \frac{1}{|\Lambda_{\text{tot}}|}\sum_{\lambda\in\Lambda_{\text{tot}}} w_\lambda (y_\lambda - \hat{y}_\lambda)^2$$



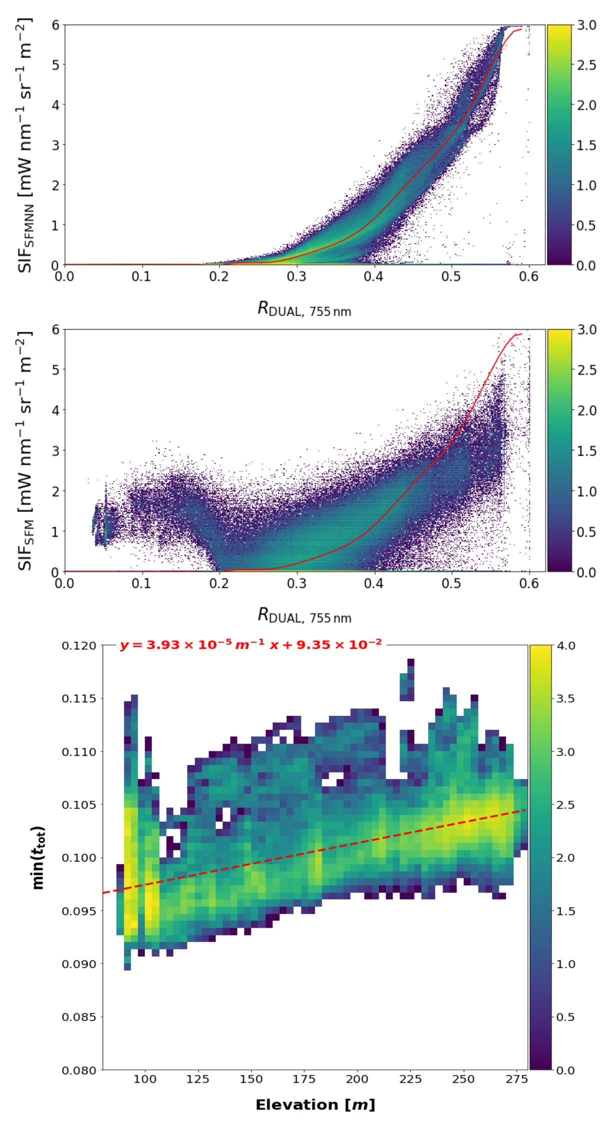
SFM baseline



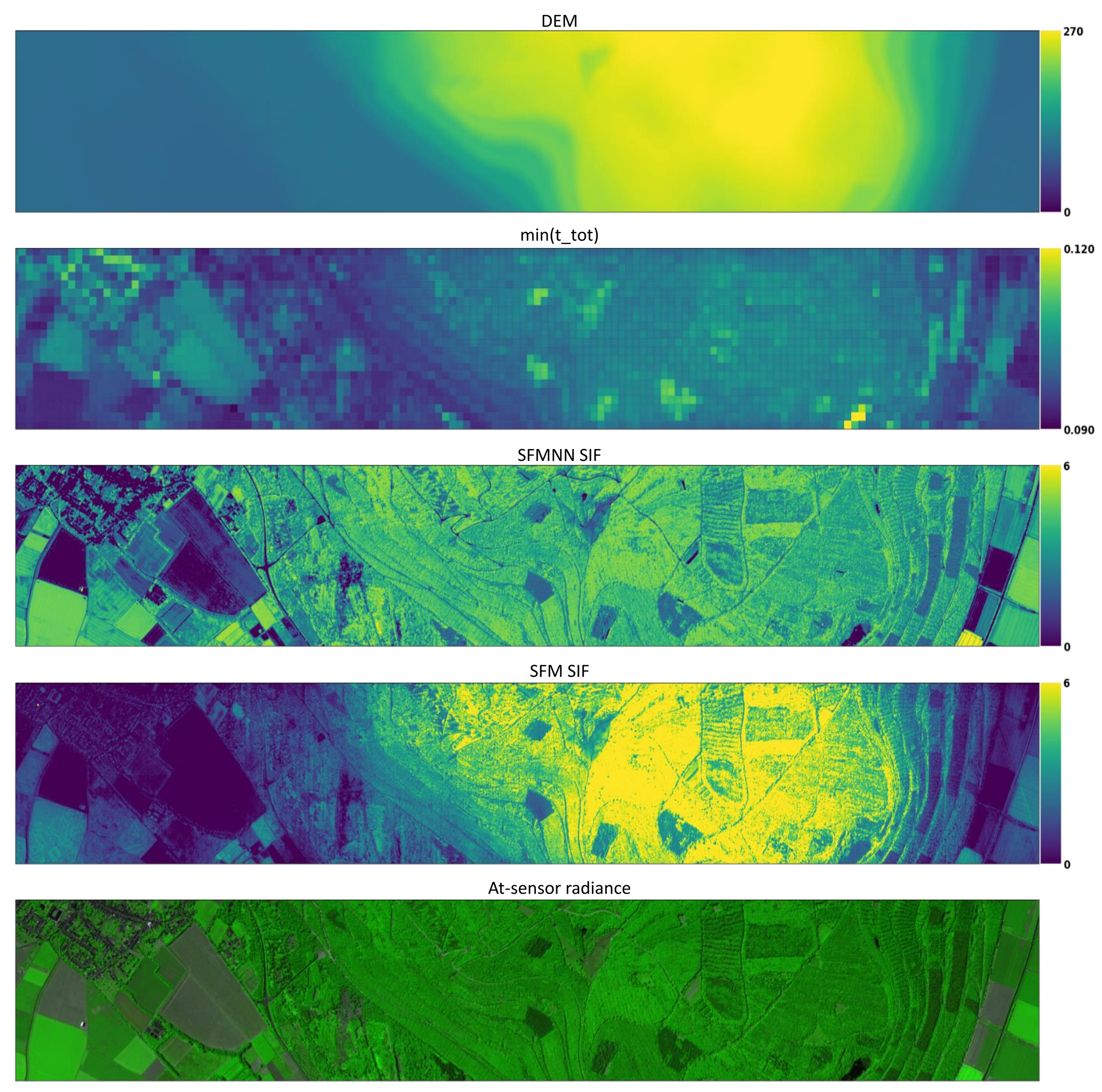
Comparison to ground measurements



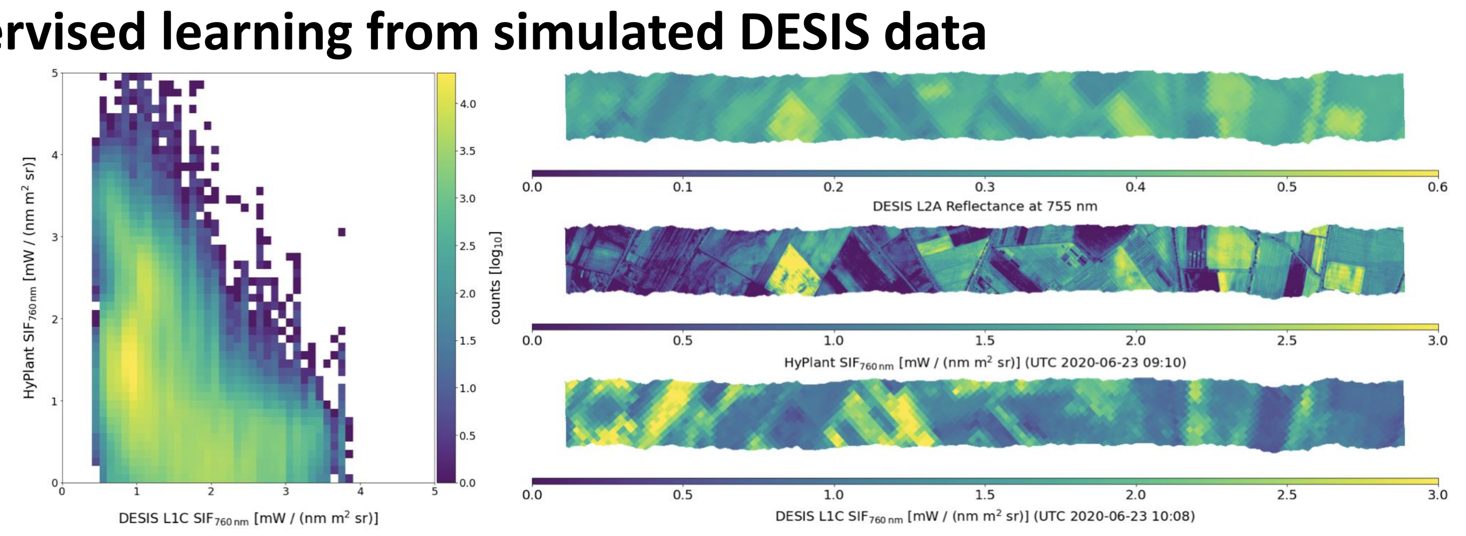
Reflectance-SIF distribution



Local estimation of atmospheric transfer function



Supervised learning from simulated DESIS data



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[1] Maier, Günther and Stellmes, ASA Special Publications (2004).
[2] Meroni et al, Remote Sensing of Environment, Vol. 113 (I. 10), p. 2037 (2009).
[3] Berk et al, Proc. SPIE 9088, 90880H (2014).
[4] Cogliati et al, Remote Sensing of Environment, Vol. 169, p. 344 (2015).

Acknowledgements

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