



Emulator-based Neural Network Prediction for SIF Retrieval in the O₂-A Absorption Band

12.06.2023

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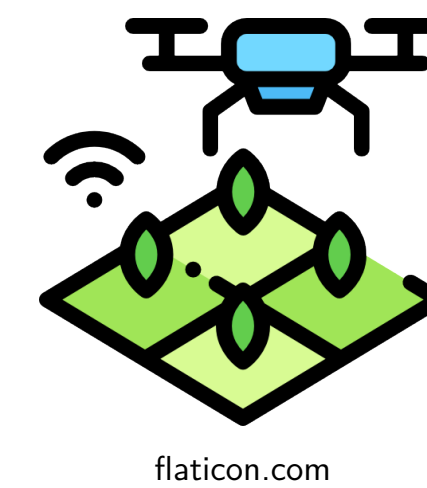
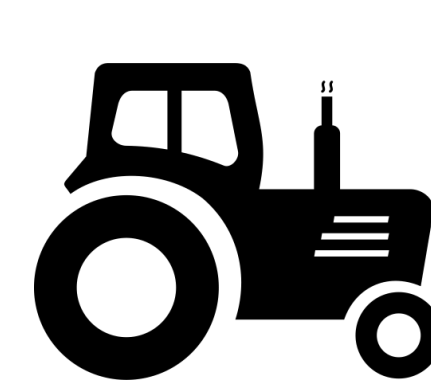
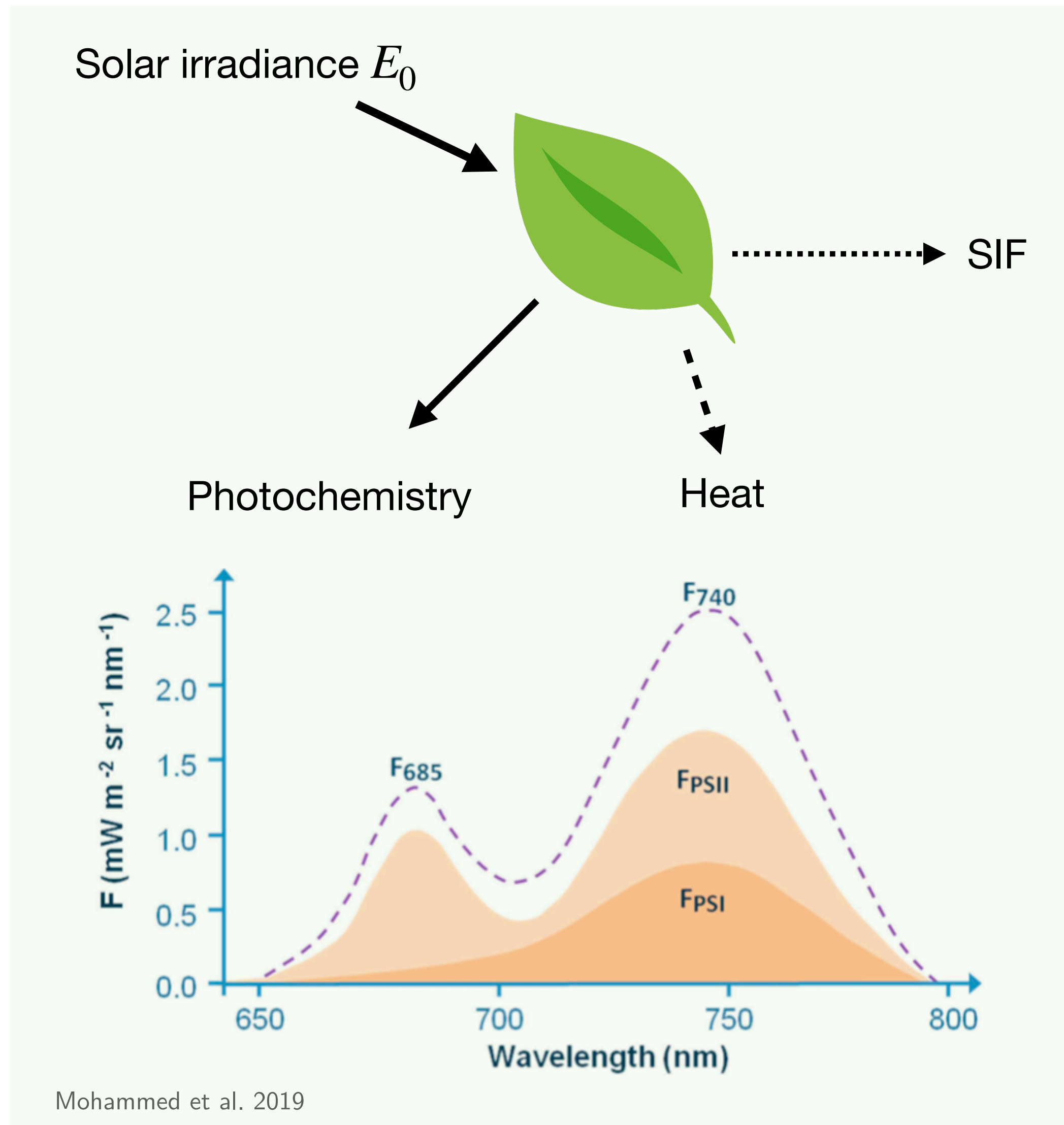
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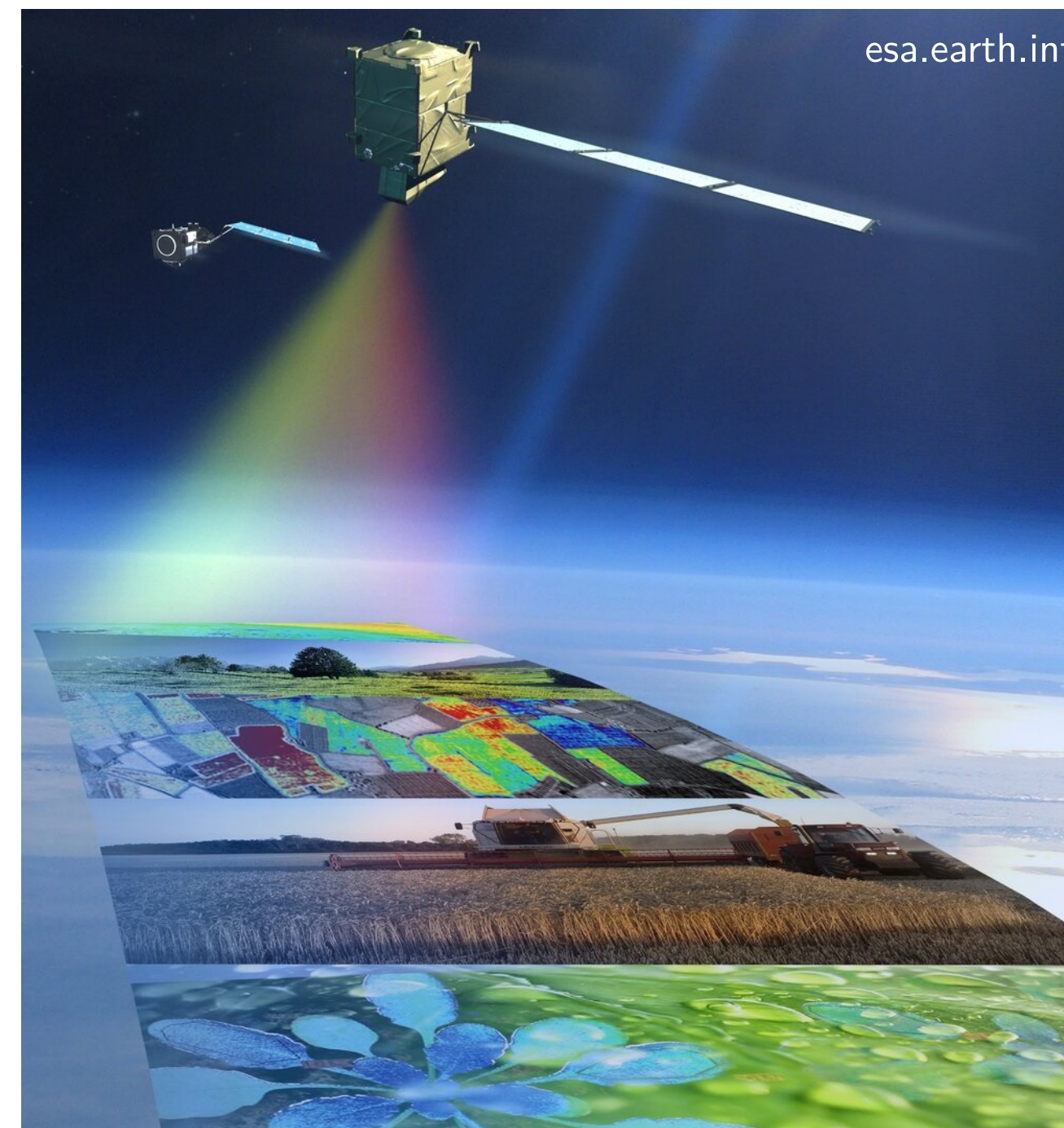
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What is Sun-Induced Fluorescence (SIF) ?



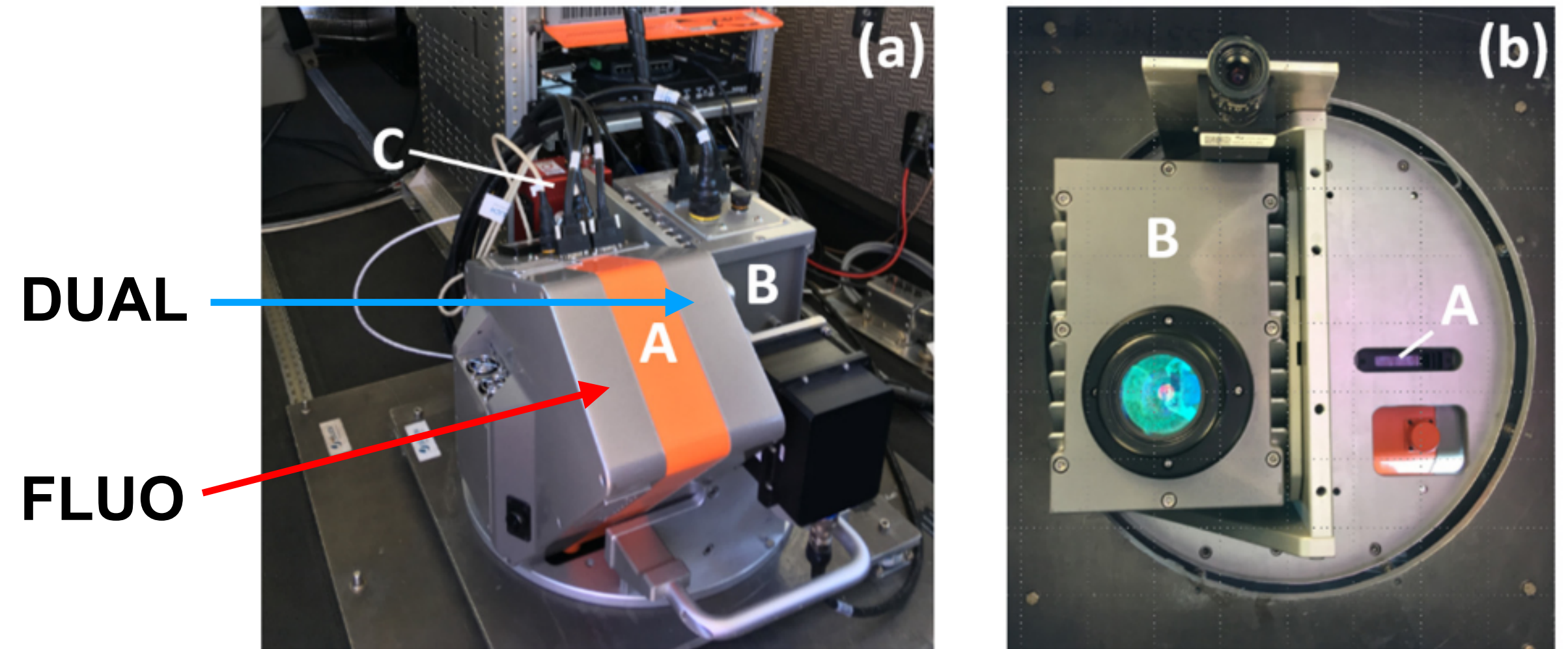
→ Agricultural use cases



→ ESA Earth Explorer FLEX
Global Fluorescence
estimations

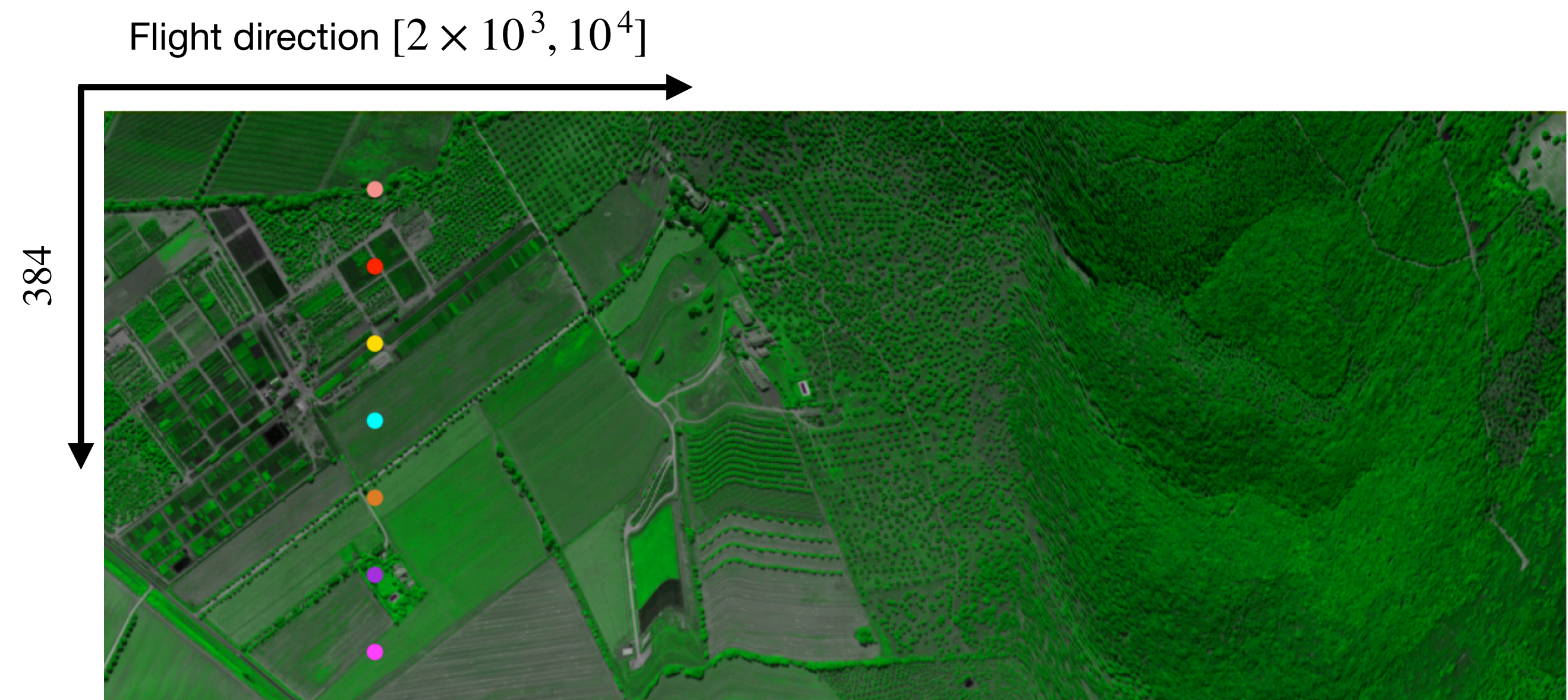
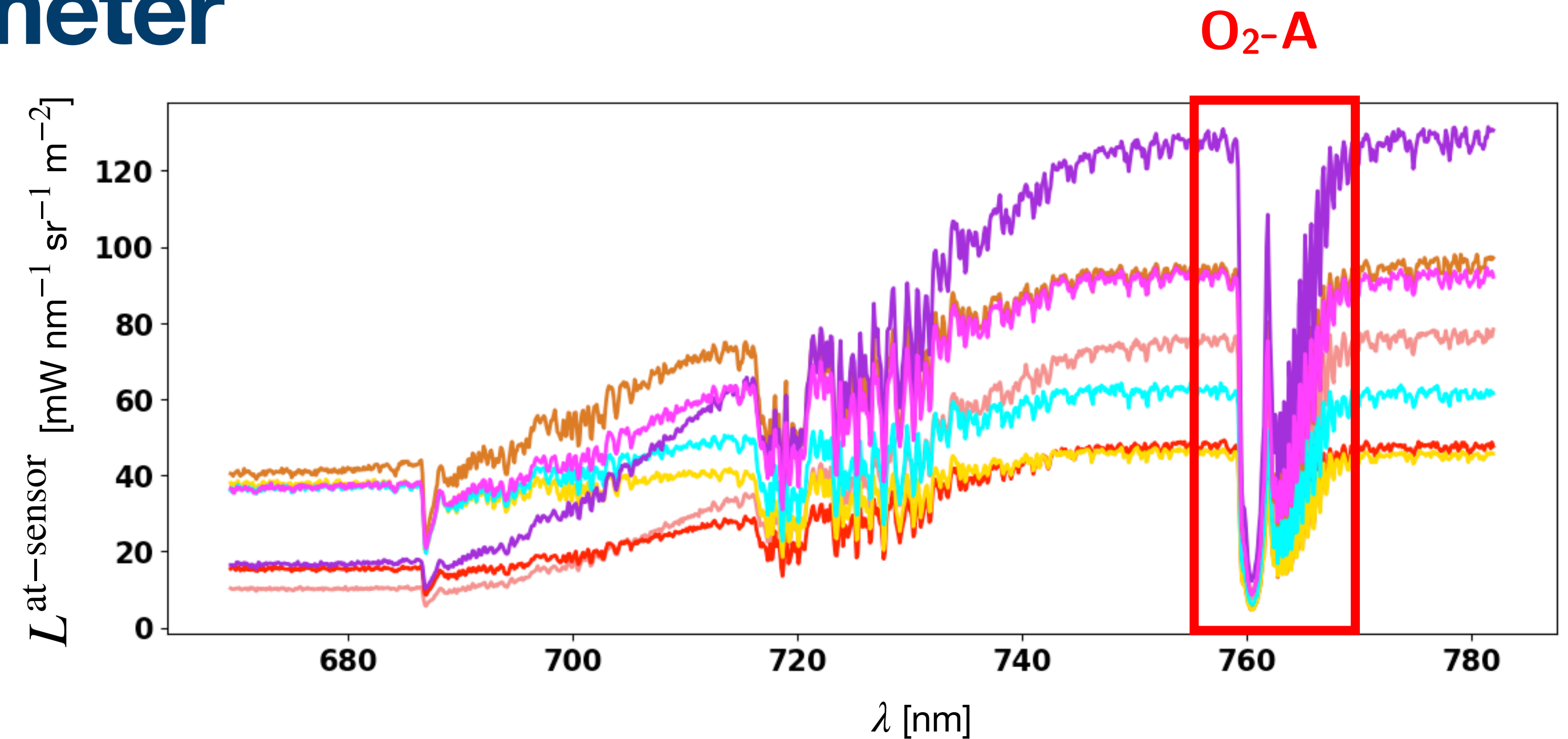
Airborne HyPlant Spectrometer

- FLUO is the **airborne demonstrator** for **FLEX**
- 0.24 nm FWHM, 0.11 nm SSI
- 5 years of comparable campaign acquisitions
- 773 acquisitions, $384 \times [2000, 10'000]$ px
- Operational Baseline SIF Retrieval Methods
 - *Spectral Fitting Method (SFM)*, Cogliati et al. 2019
 - *Improved Fraunhofer Line Discrimination (iFLD)*, Damm et al. 2022



Airborne HyPlant Spectrometer

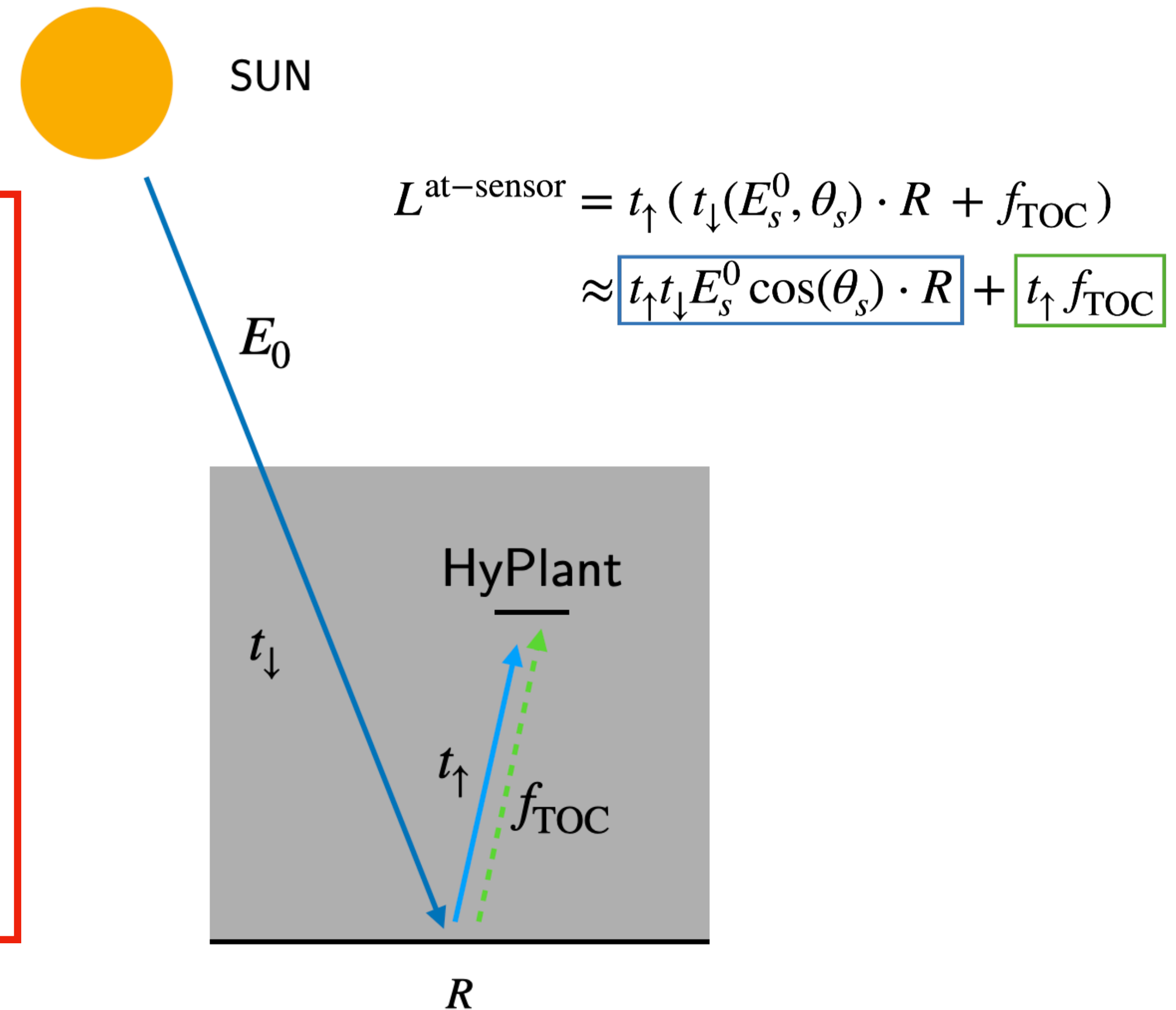
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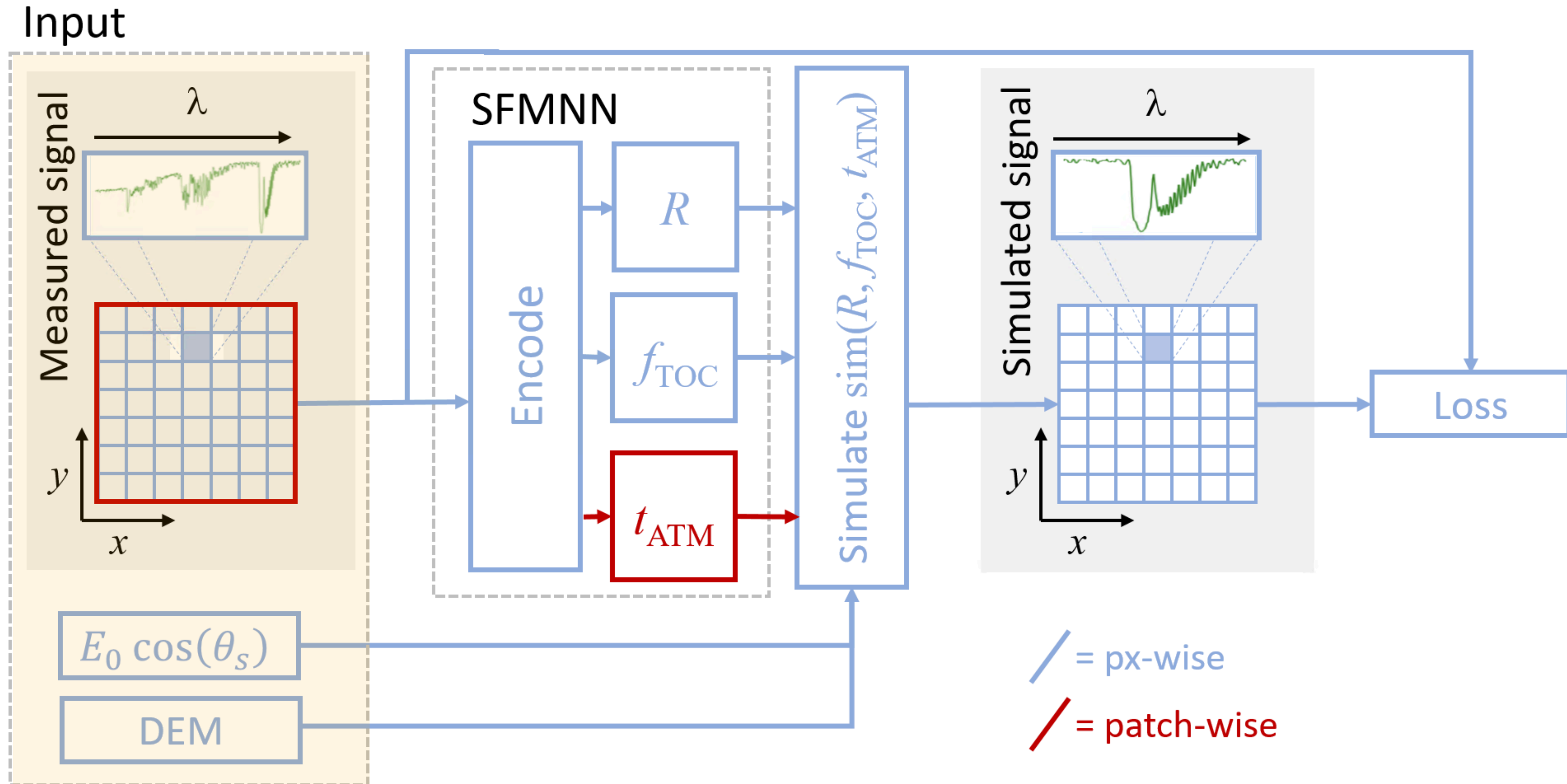
Spectral Fitting Methods to Retrieve Fluorescence

- Conventional **Least Squares Optimization** in Spectral Fitting Method (SFM)

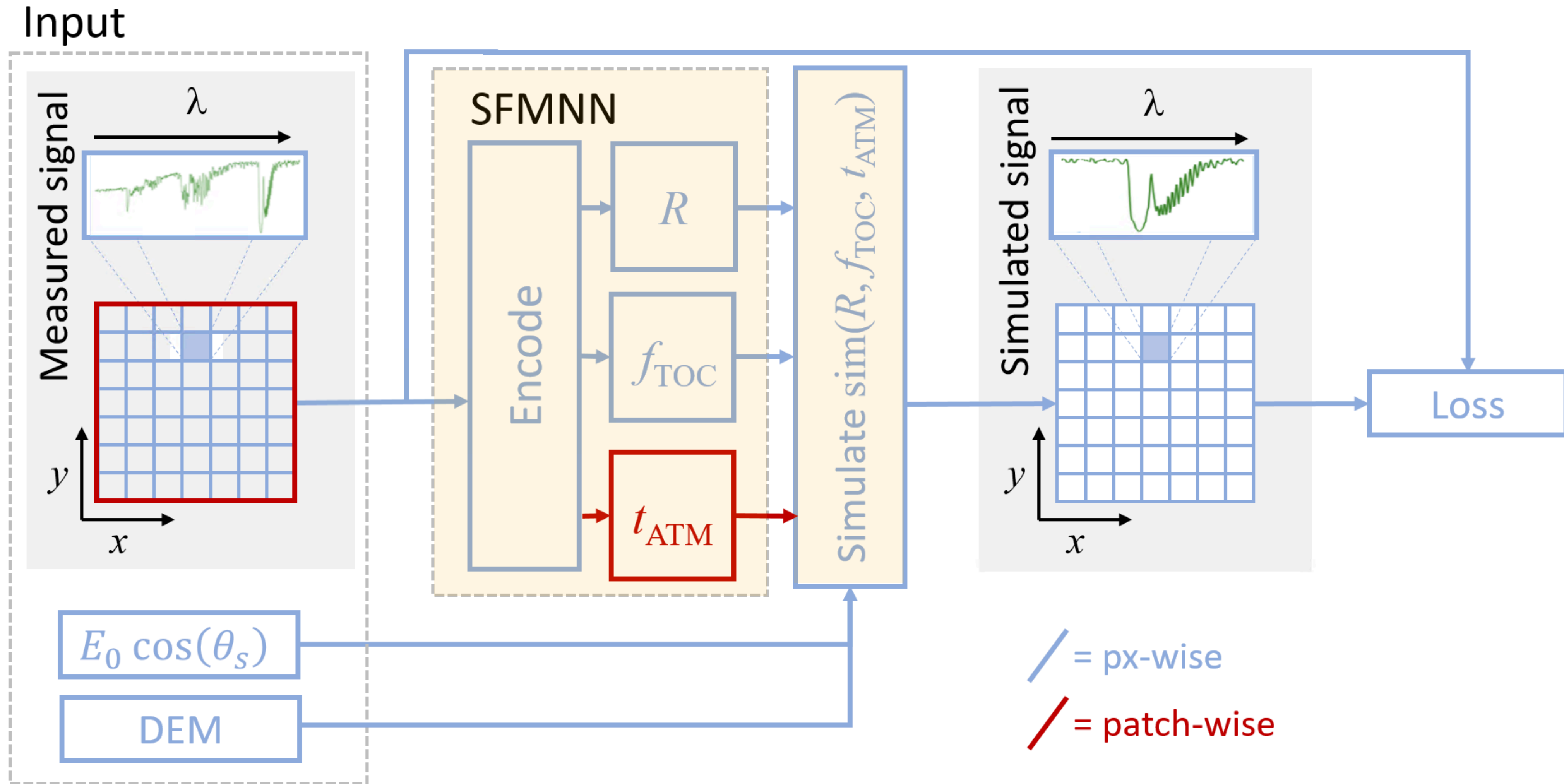
- Data inefficiency:*
no benefits from **statistical relationships**
- Slow:*
Individual fit of each spectral pixel
- Model failure:*
in **topographically variable terrain**



Spectral Fitting Method Neural Network (SFMNN)



Spectral Fitting Method Neural Network (SFMNN)



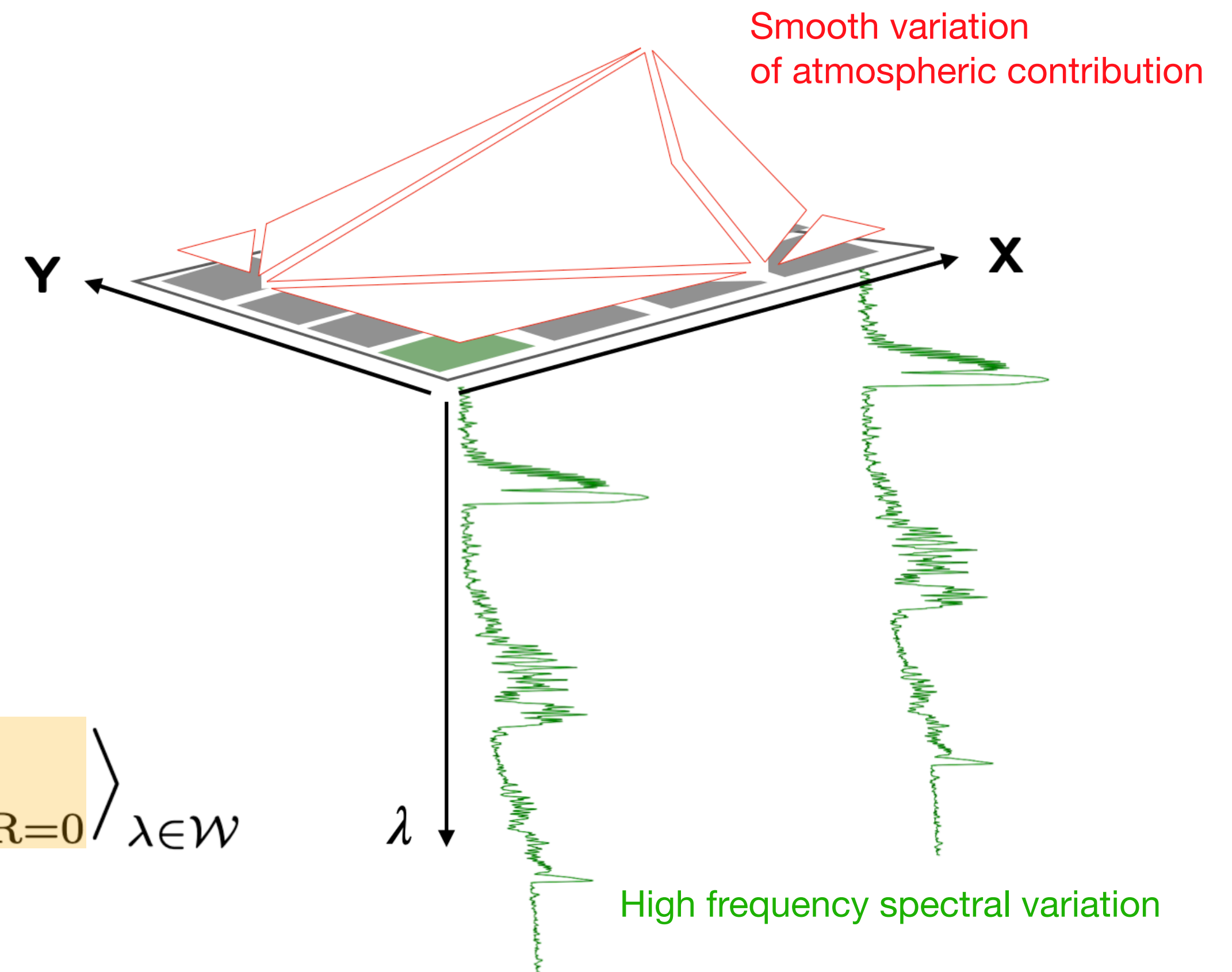
Loss and Constraint Formulation

Self-Supervised Loss Formulation for Signal Reconstruction

- Inversion under incomplete knowledge of physical process is **ill-posed**.
- Architectural **constraint** formulation: difference in spatial variation of terms contributing to radiance signal

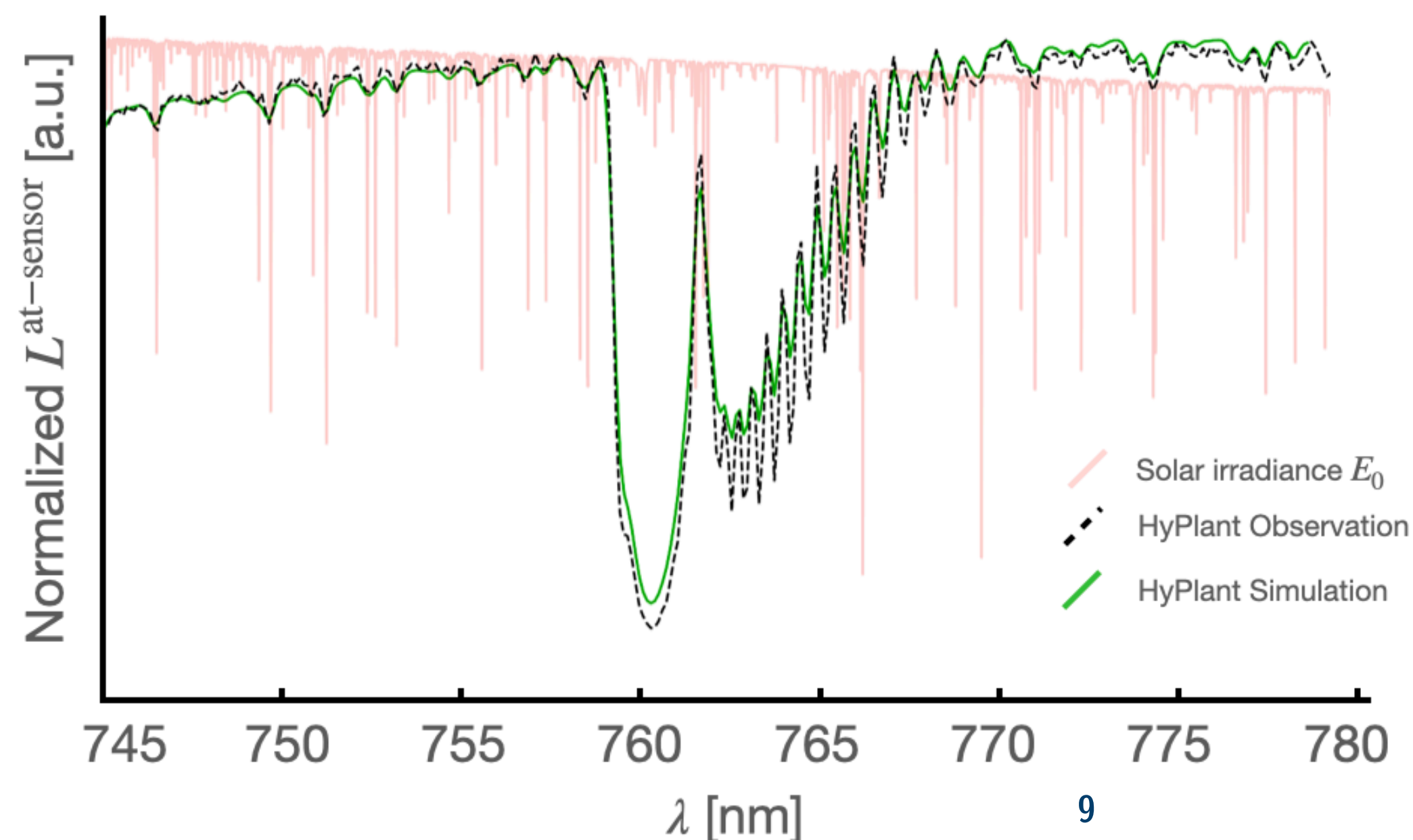
$$\begin{aligned}
 \ell(y, \hat{y}) &= (\ell_{R,f} + \gamma_f \ell_f + \gamma_N \ell_{\text{NDVI}})(y, \hat{y}) \\
 &= \left\langle (y(\lambda) - \hat{y}(\lambda))^2 + \gamma_f \left(w_\lambda (y(\lambda) - \hat{y}(\lambda))^2 \right)_{\delta R=0} \right\rangle_{\lambda \in \mathcal{W}} \\
 &\quad + \gamma_N \hat{f} \delta(\text{NDVI}_y \leq t)
 \end{aligned}$$

Overall residual
 SNR weighting
 Physiological constraint



Simulation of HyPlant At-sensor Radiance

- Radiative Transfer Modelling (MODTRAN)
- Extensive coverage of observational conditions
- Inclusion of topographic variation

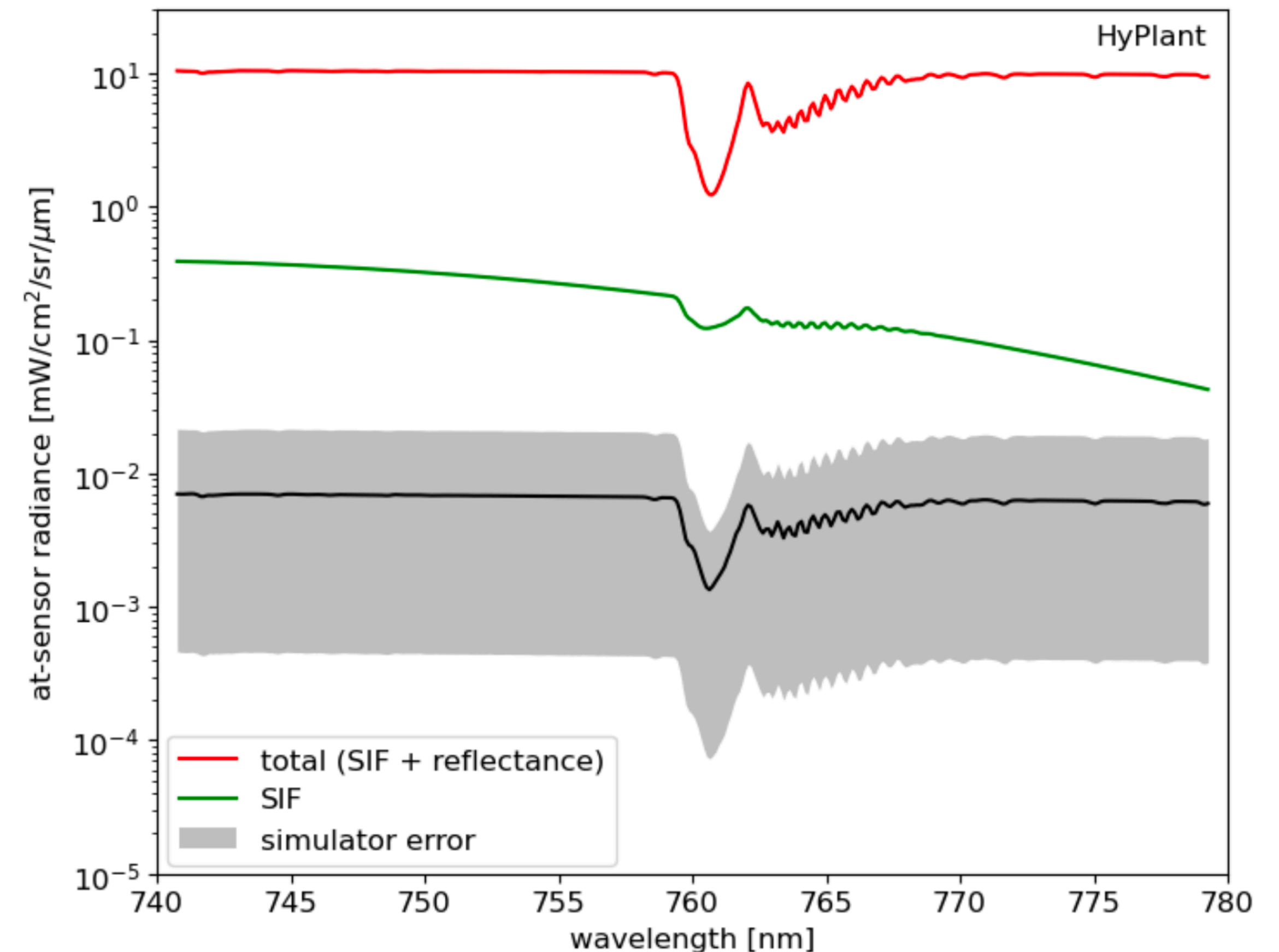


13 parameters

Parameter		HyPlant DB
Atmosphere	model	mid-latitude summer
	H ₂ O [cm]	0.3–3.0
	O ₃ [DU]	332
	AOT ₅₅₀ []	0.05–0.40
	aerosol model	rural
	g []	[−1, +1]
Geometry	TA [°]	0–20
	SZA [°]	20–55
	RAA [°]	0–180
	h_{gnd} [m]	0–300
	h_{sen} [km]	0.659–0.691 agl 1.543–1.598 agl
Surface	ρ_{740} []	0.05–0.60
	$d\rho/d\lambda$ [nm ^{−1}]	0–0.008
	F_{737}/F_0	0–8
Sensor	δ_λ [nm]	[−0.080, +0.023]
	δ_{FWHM} [nm]	[−0.040, +0.040]

Emulation of HyPlant At-sensor Radiance

- High-dimensional regression problem (13 $\rightarrow$ 349 dims)
- A set of regression models were tested
- Polynomial of 4th degree (P4) is precise enough
- P4 was used as forward simulator in SFMNN

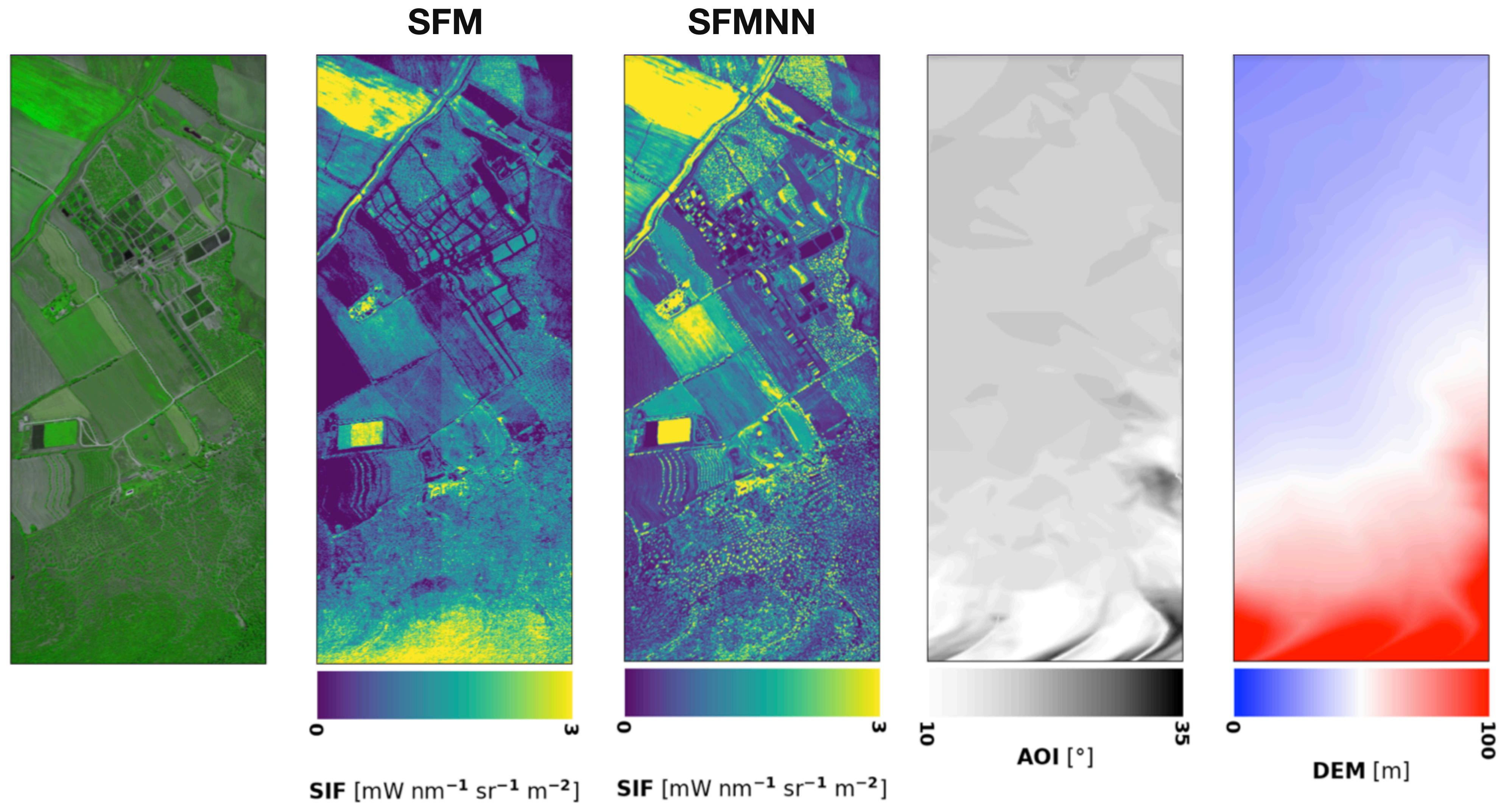


Comparison with in-situ measurements

- Small set of synchronous SIF ground measurements
- Good correlation
- Absolute errors impacted by systematic biases
- Might be caused by domain gap between simulations and HyPlant observations

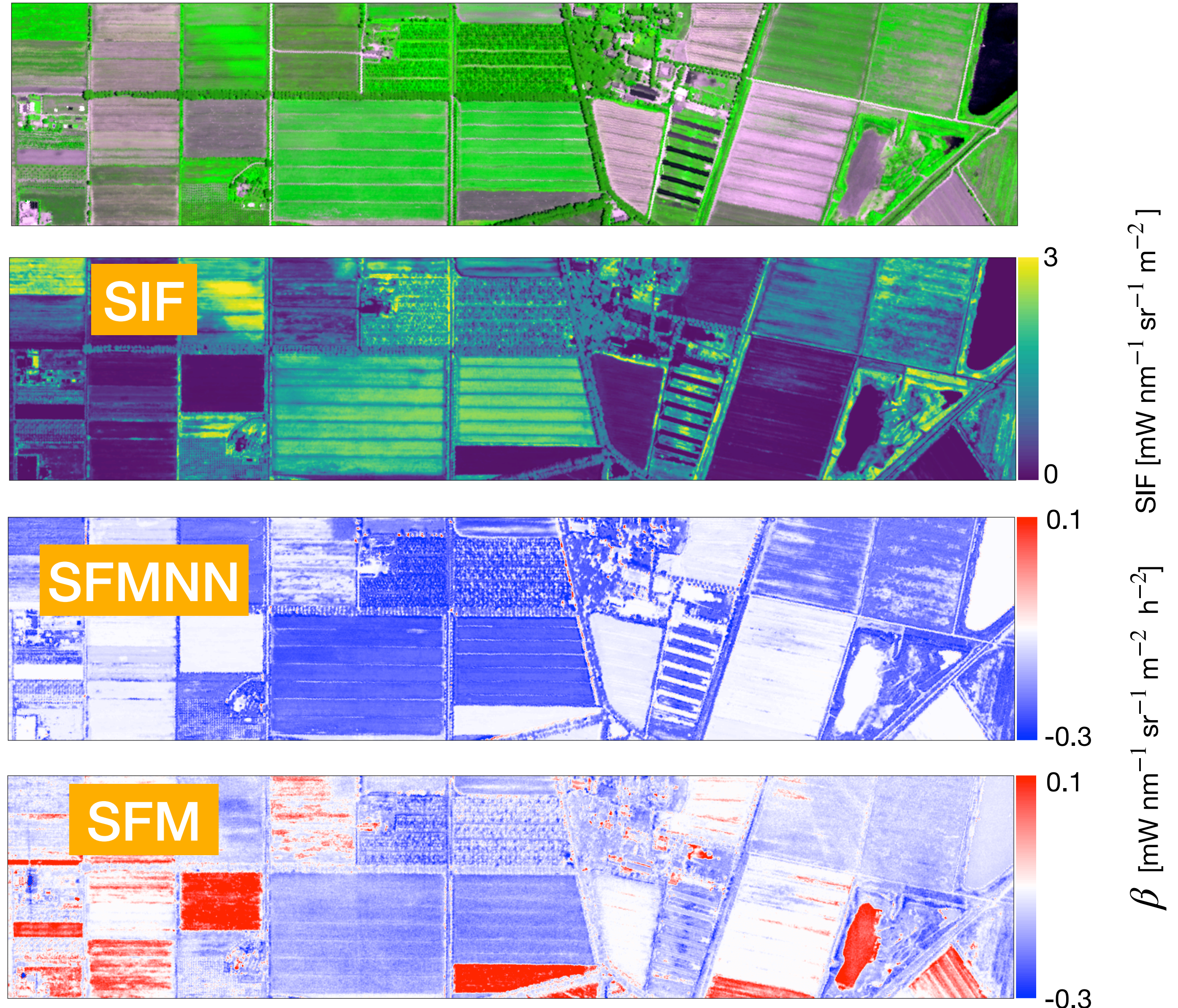
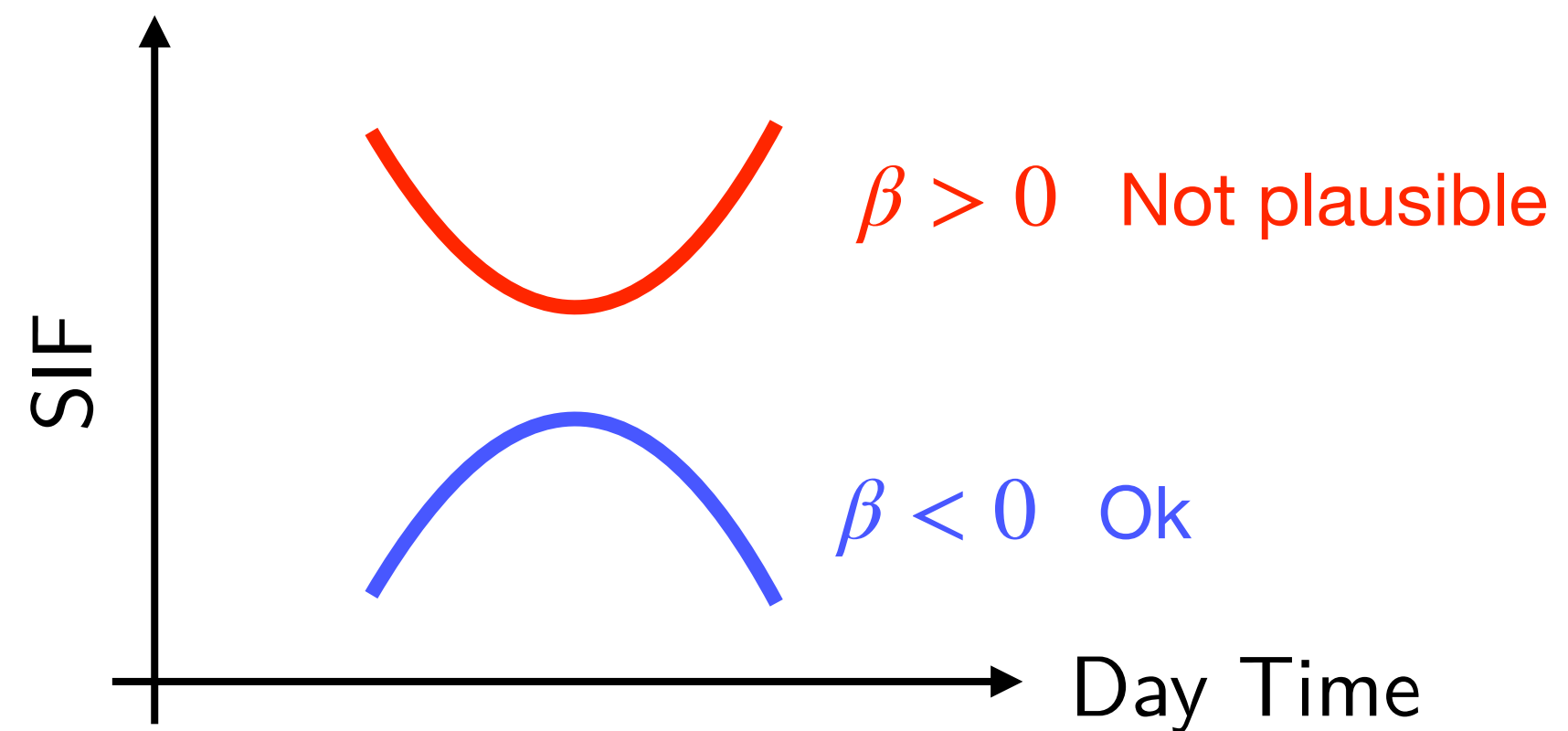
Data Set		r^{pear}	MAE mW nm ⁻¹	MAE[calib] m ⁻² sr ⁻¹	N
CKA-2020 (600m)	SFM	0.85	0.43 ± 0.05	0.17 ± 0.02	18
	SFMNN	0.78	0.90 ± 0.03	0.18 ± 0.04	18
	iFLD	0.53	0.41 ± 0.07	0.24 ± 0.01	18
SEL-2018 (600m)	SFM	0.91	0.53 ± 0.07	0.11 ± 0.00	12
	SFMNN	0.93	0.40 ± 0.03	0.11 ± 0.00	12
	iFLD	0.82	0.61 ± 0.09	0.18 ± 0.00	12

SIF Prediction in Topographically Variable Terrain



Diurnal SIF Dynamics are phenologically plausible

- Time series from repeated flights
- Second order derivative β as a measure for diurnal SIF dynamics



Conclusions & Outlook

- The emulator-based neural network prediction achieves correlation comparable to SFM on a data set of in-situ measurements.
- Further analysis is needed to establish the reasons for systematic errors in absolute SIF prediction.
- The impact of the topographic variation on the atmospheric transfer is compensated in SFMNN.
- SFMNN predicted diurnal SIF dynamics are physiologically plausible.
- The possibility to extend this method to other sensors is currently being evaluated:
 - DESIS (onboard the ISS) in FluoMap
 - FLEX, simulated hyperspectral imagery

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The authors gratefully acknowledge the computing time granted through JARA on the supercomputer JURECA[1] at Forschungszentrum Jülich.

[1] Jülich Supercomputing Centre. (2021). JURECA: Data Centric and Booster Modules implementing the Modular Supercomputing Architecture at Jülich Supercomputing Centre Journal of large-scale research facilities, 7, A182. <http://dx.doi.org/10.17815/jlsrf-7-182>

