Emulator-based Neural Network Prediction for SIF Retrieval in the O_2-A Absorption Band

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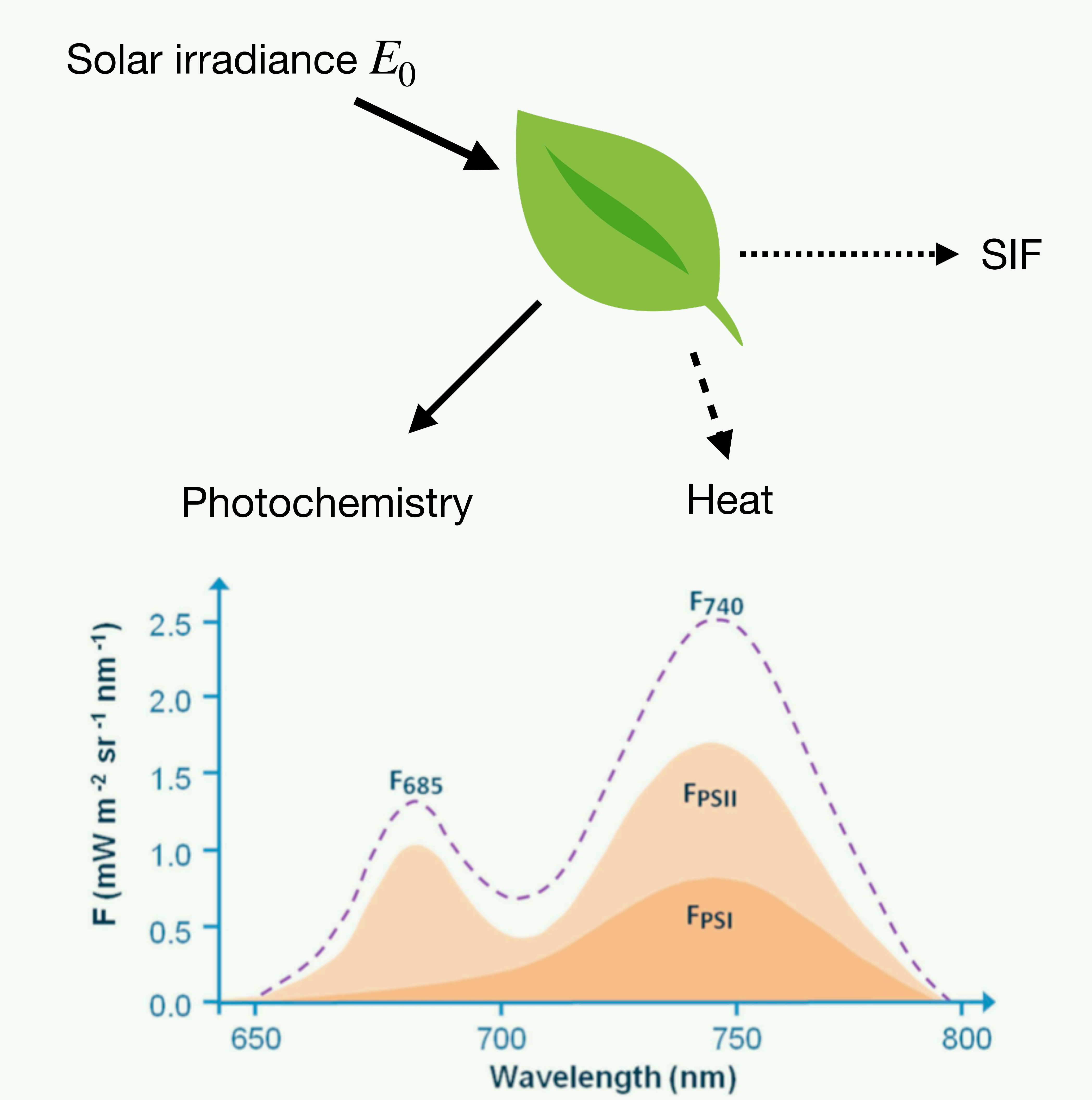
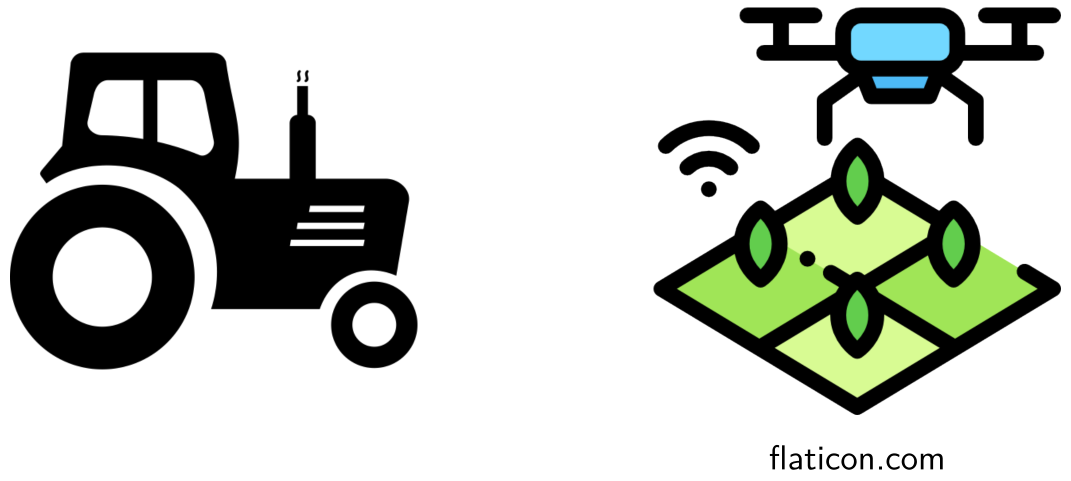
FluoMap: a Helmholtz AI funded project

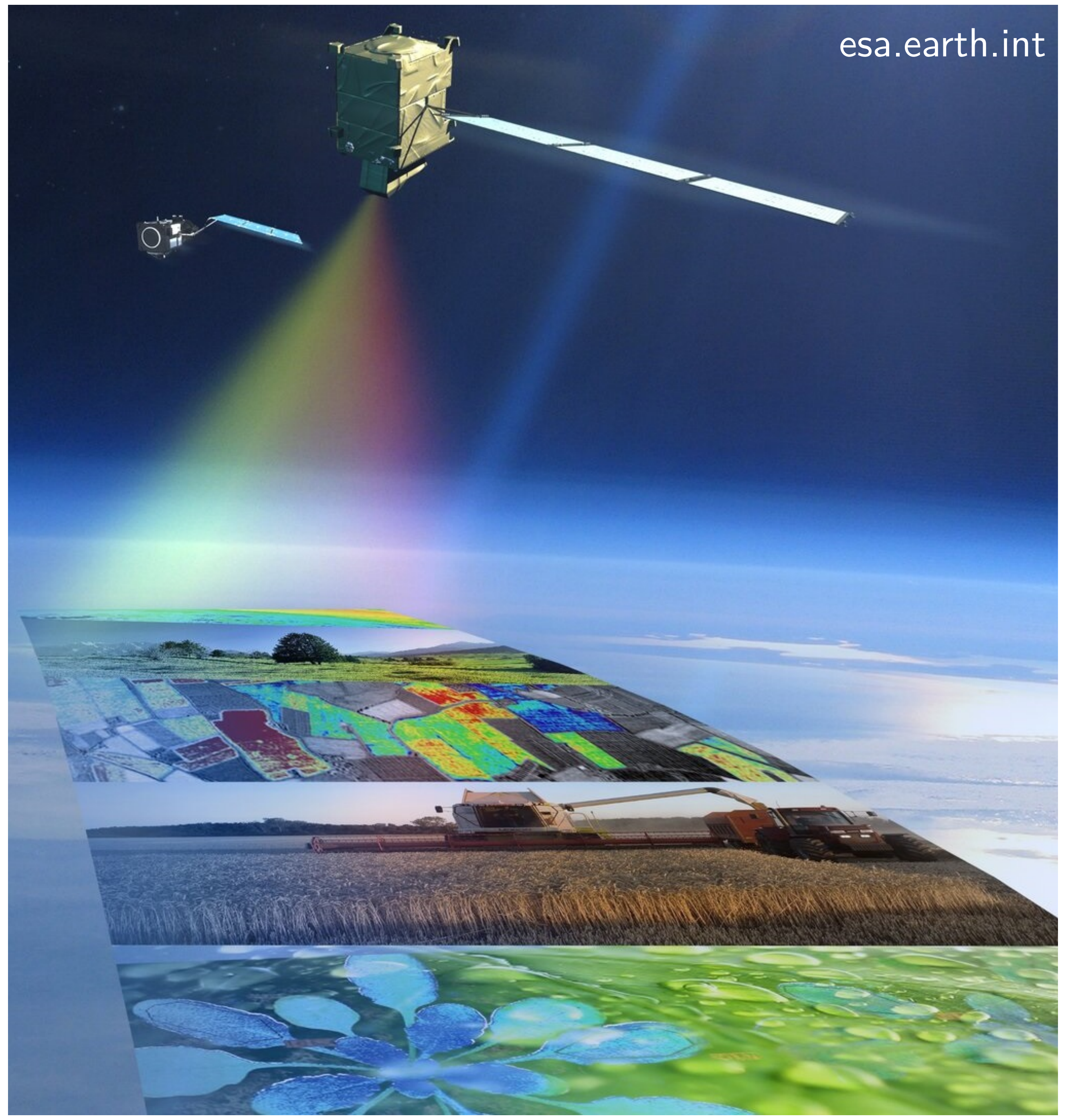
What is Sun-Induced Fluorescence (SIF) ?



Mohammed et al. 2019



→ Agricultural use cases



→ ESA Earth Explorer FLEX Global Fluorescence estimations

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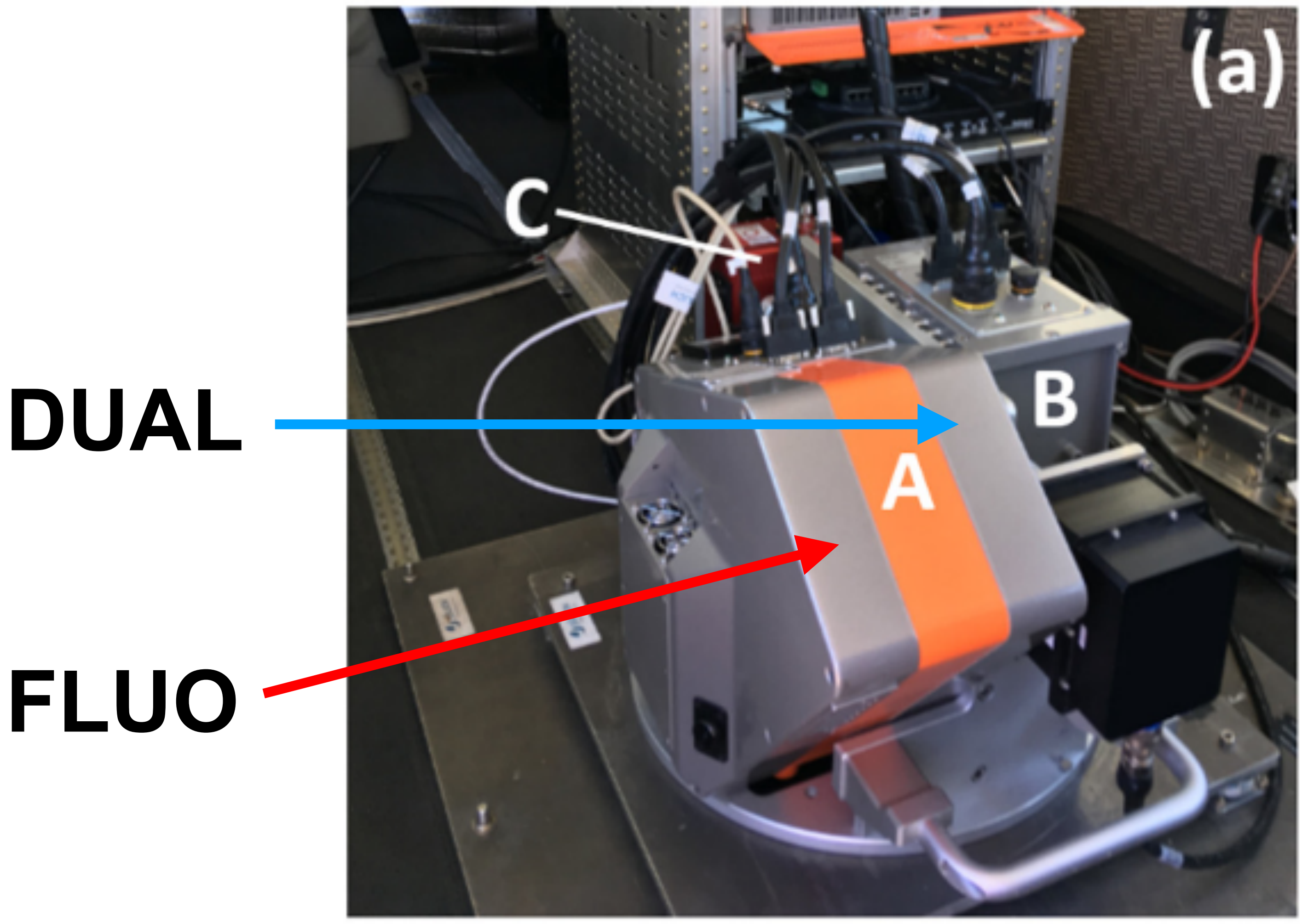
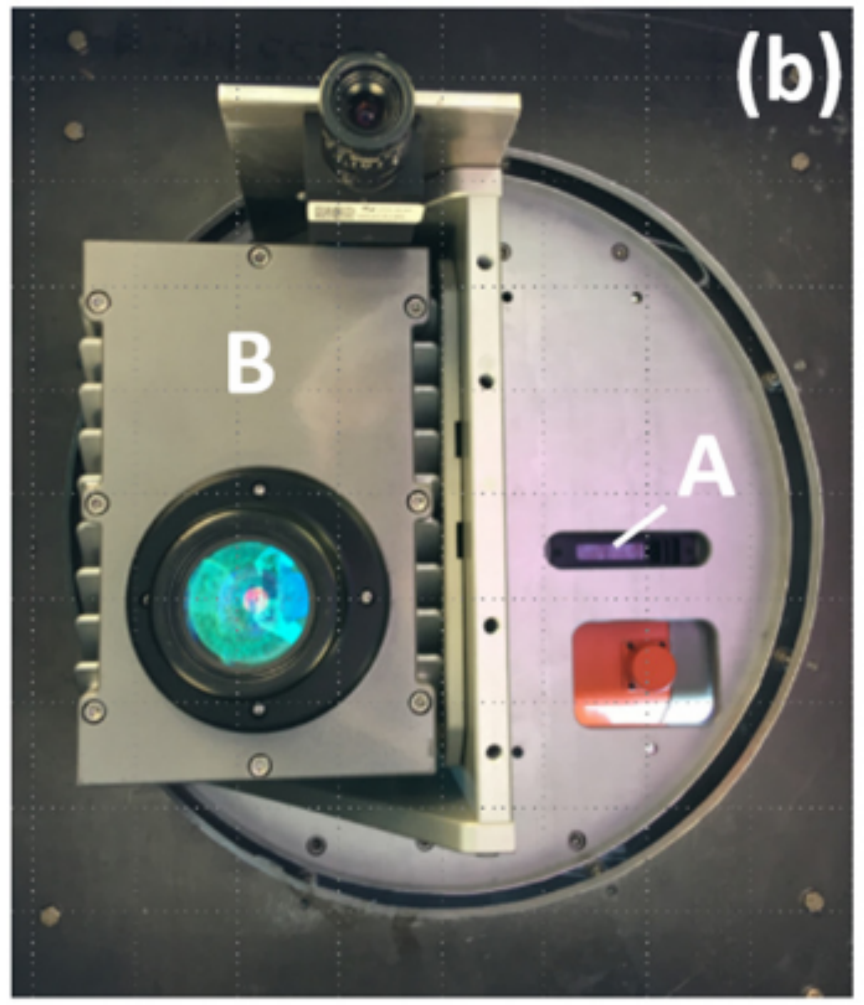
Airborne HyPlant Spectrometer

- FLUO is the **airborne demonstrator** for **FLEX**
- 0.24 nm FWHM, 0.11 nm SSI
- 5 years of comparable campaign acquisitions
- 773 acquisitions, 384 × [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





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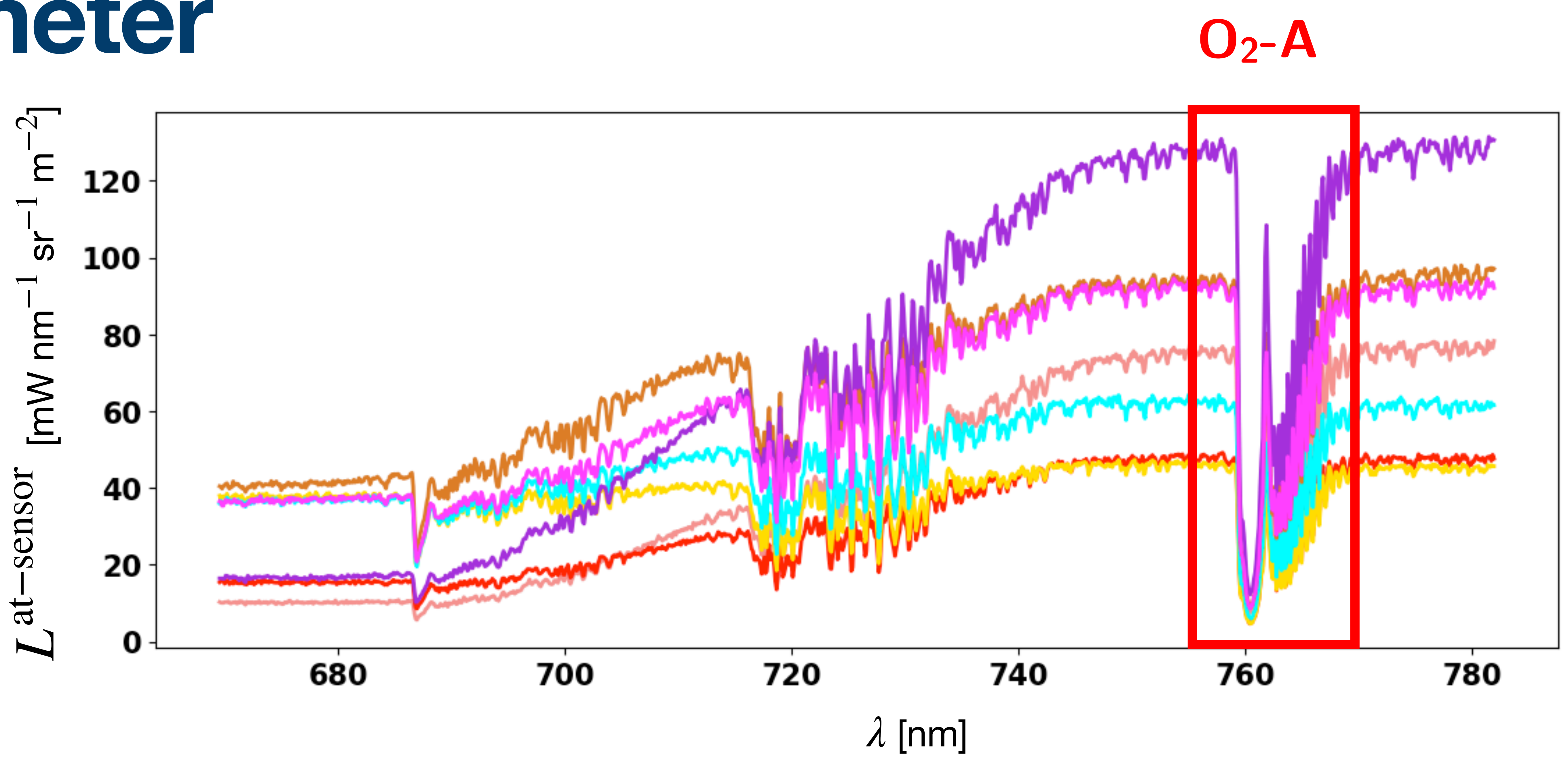
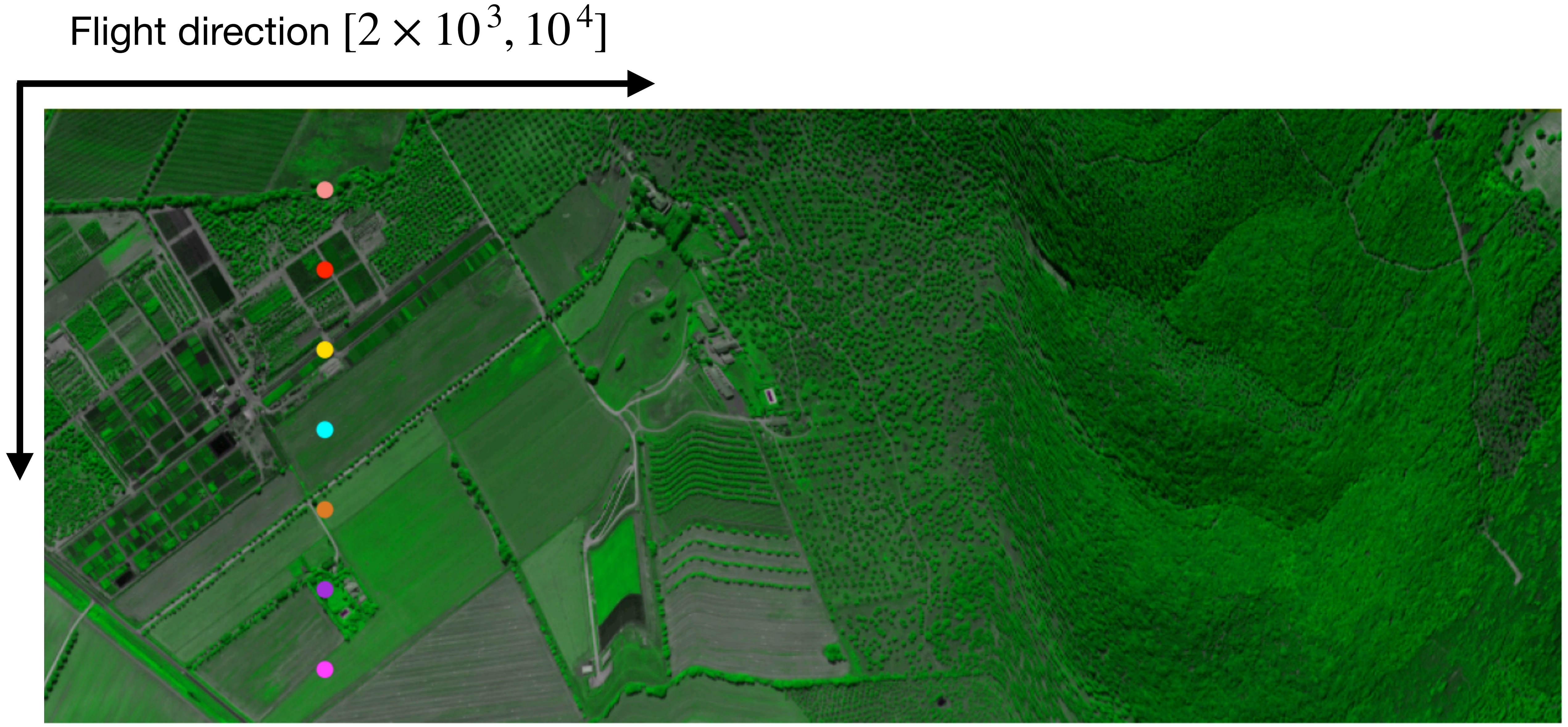
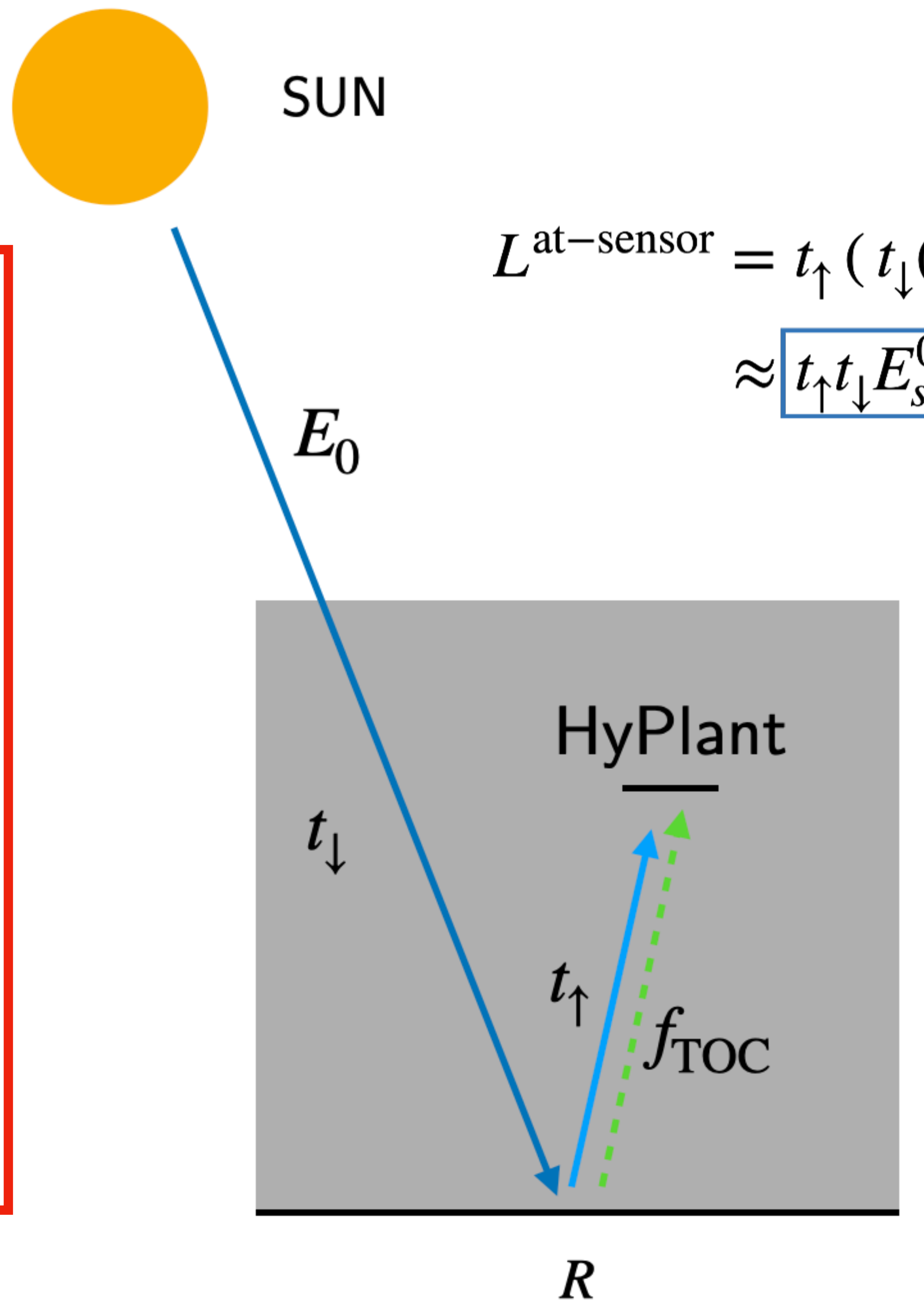




Spectral Fitting Methods to Retrieve Fluorescence

- 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**



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

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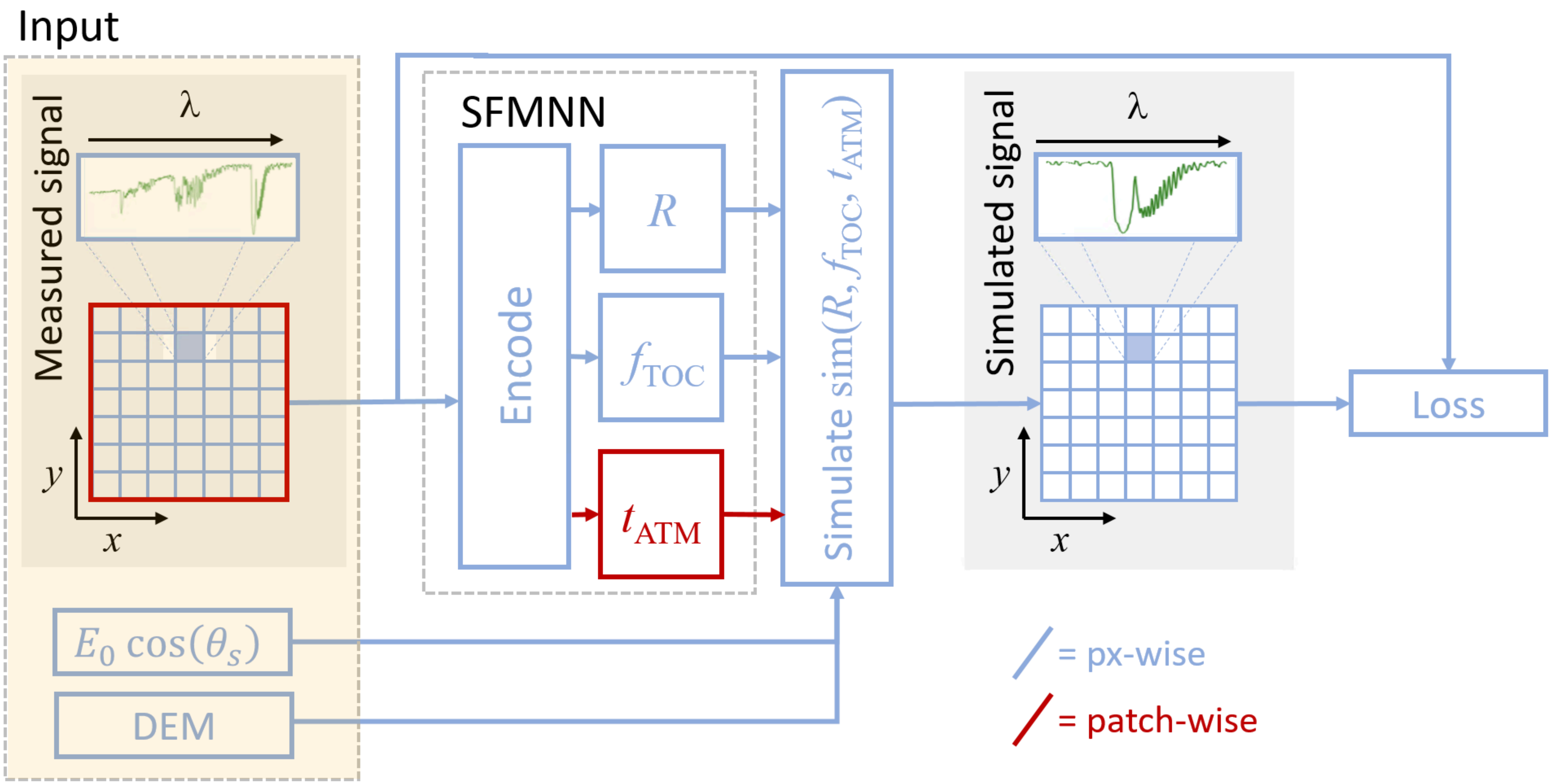
Spectral Fitting Method Neural Network (SFMNN)



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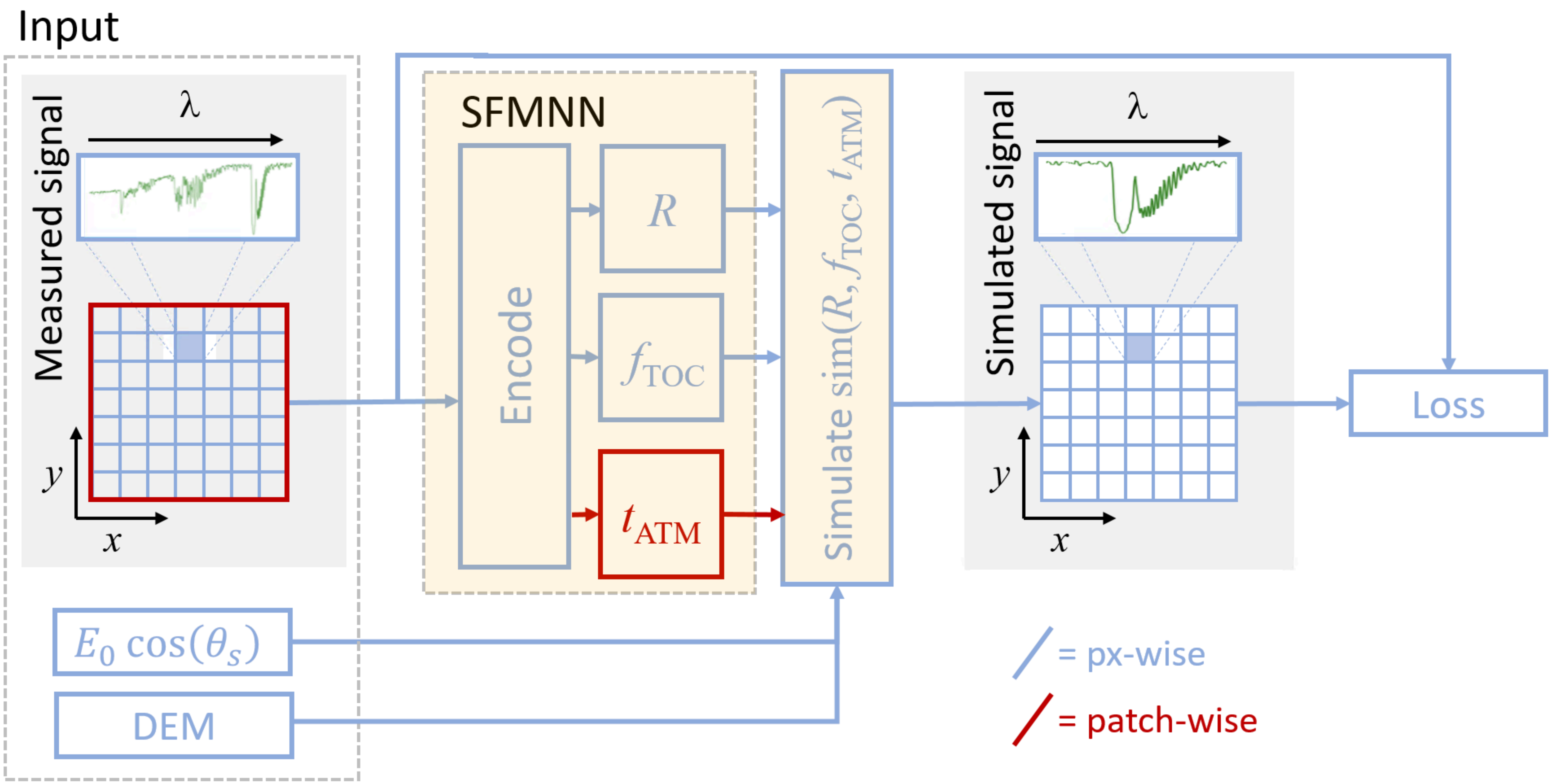

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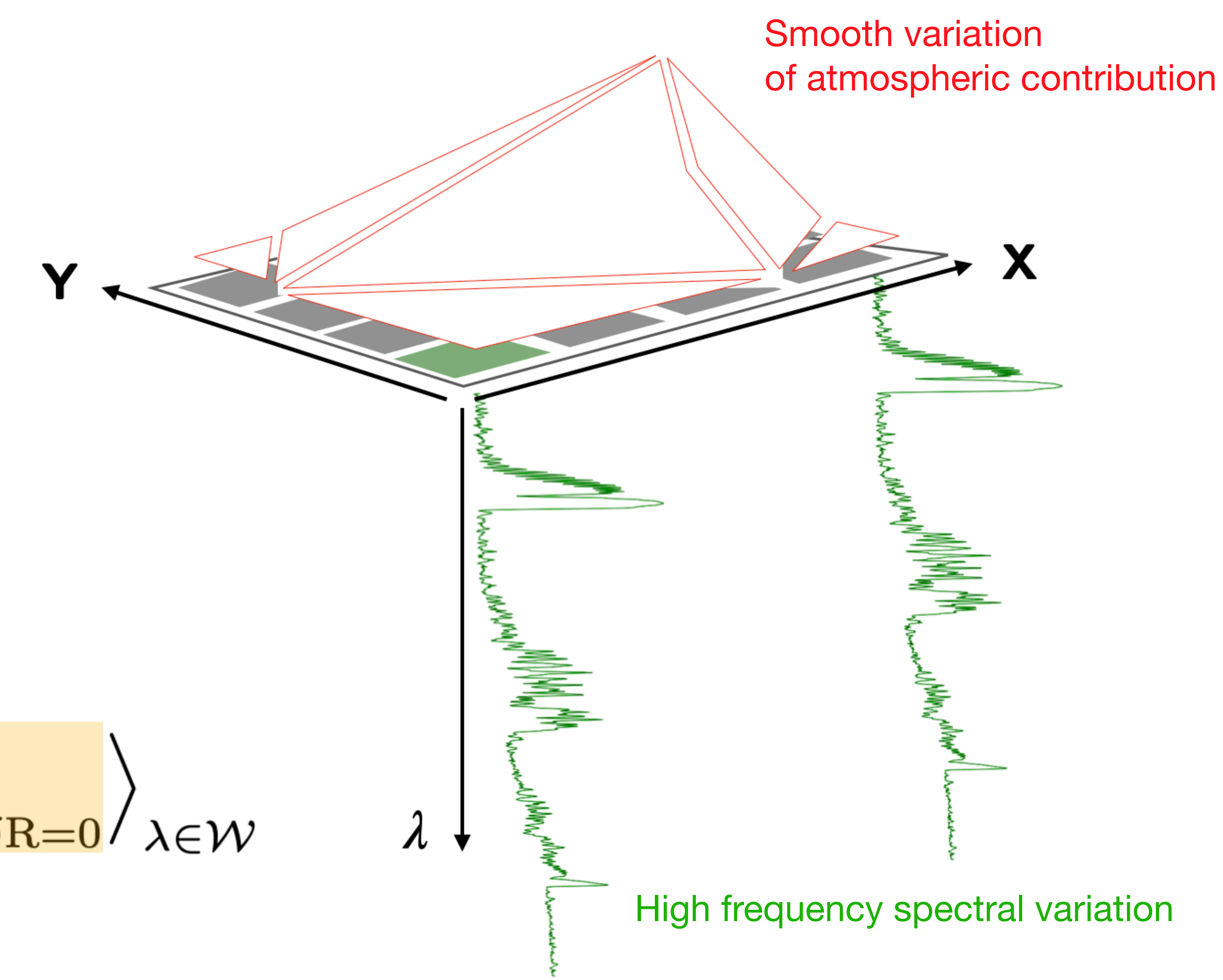
Loss and Constraint Formulation

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



$$\ell(y,\hat{y}) = (\ell_{R,f} + \gamma_f\, \ell_f + \gamma_N\, \ell_{\mathrm{NDVI}})(y,\, \hat{y})$$

$$= \left\langle (y(\lambda) - \hat{y}(\lambda))^2 + \gamma_{\mathrm{f}} \left(w_\lambda \left(y(\lambda) - \hat{y}(\lambda)\right)^2 \right)_{\delta\mathrm{R}=0} \right\rangle_{\lambda\in\mathcal{W}}$$

$$+ \; \gamma_{\mathrm{N}}\; \hat{f}\; \delta\left(\mathrm{NDVI}_y \leq\; t\right)$$

Overall residual SNR weighting Physiological constraint

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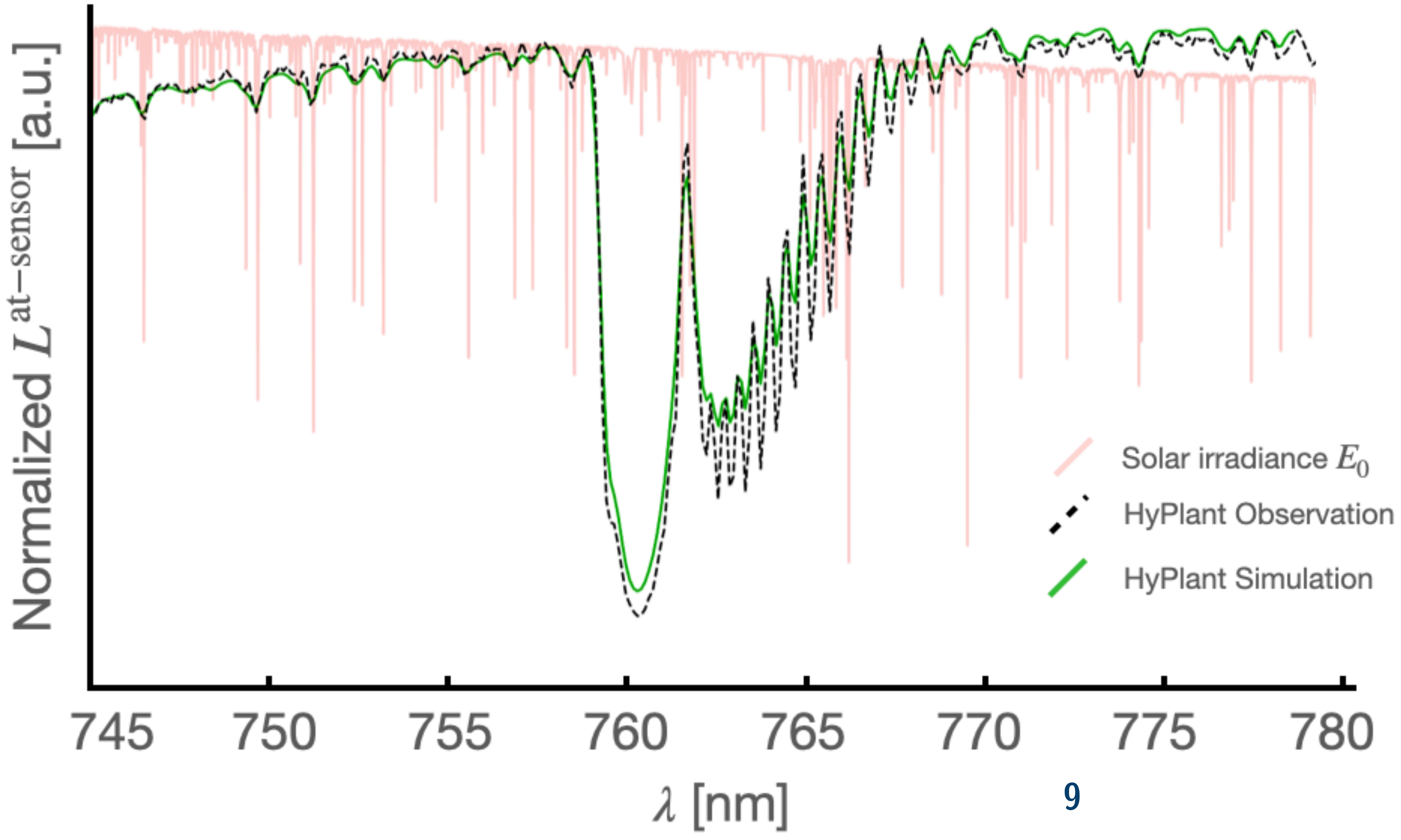
Simulation of HyPlant At-sensor Radiance

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

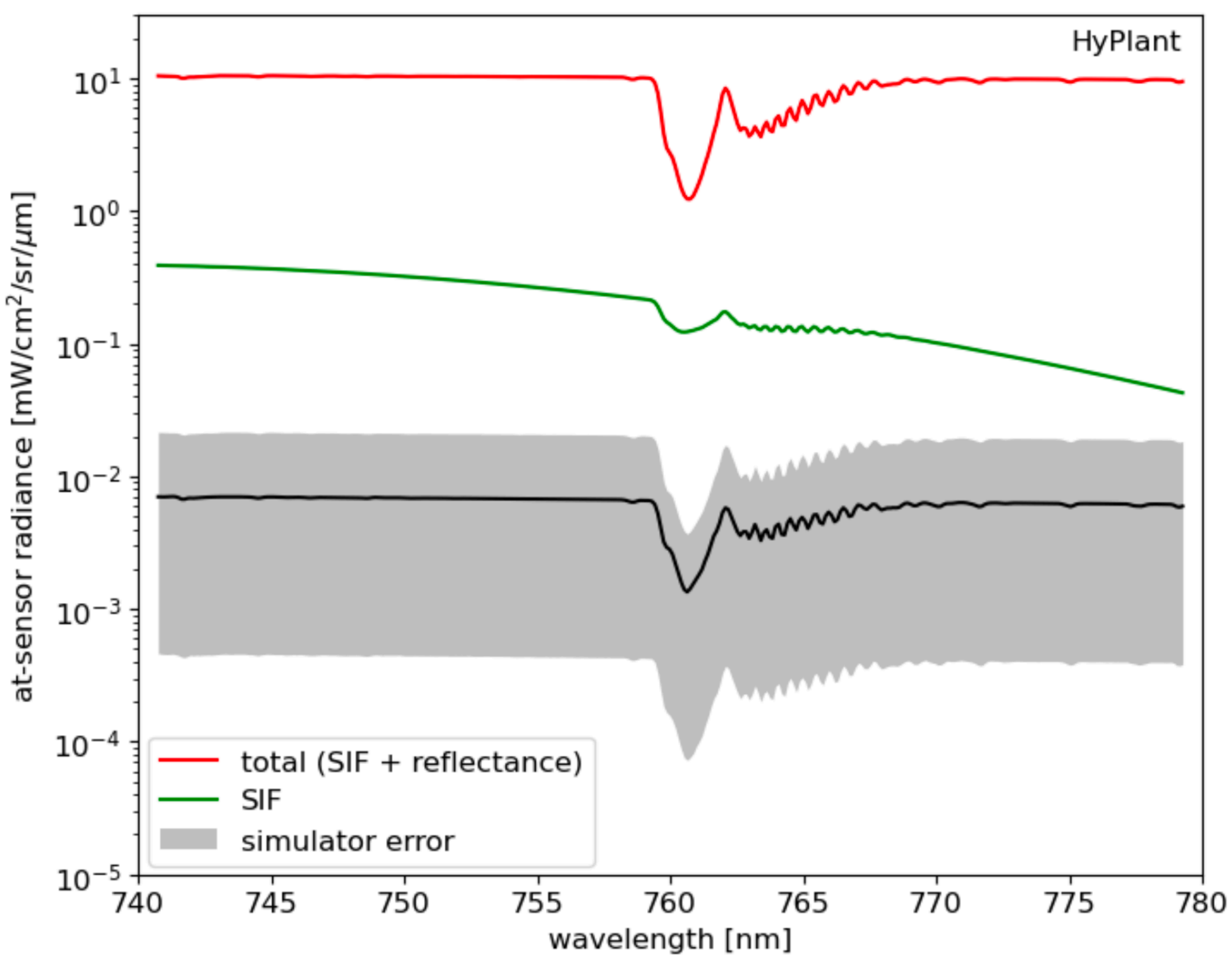


13 parameters

Parameter		HyPlant DB
Atmosphere	model	mid-latitude summer
	H_2O [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 → 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



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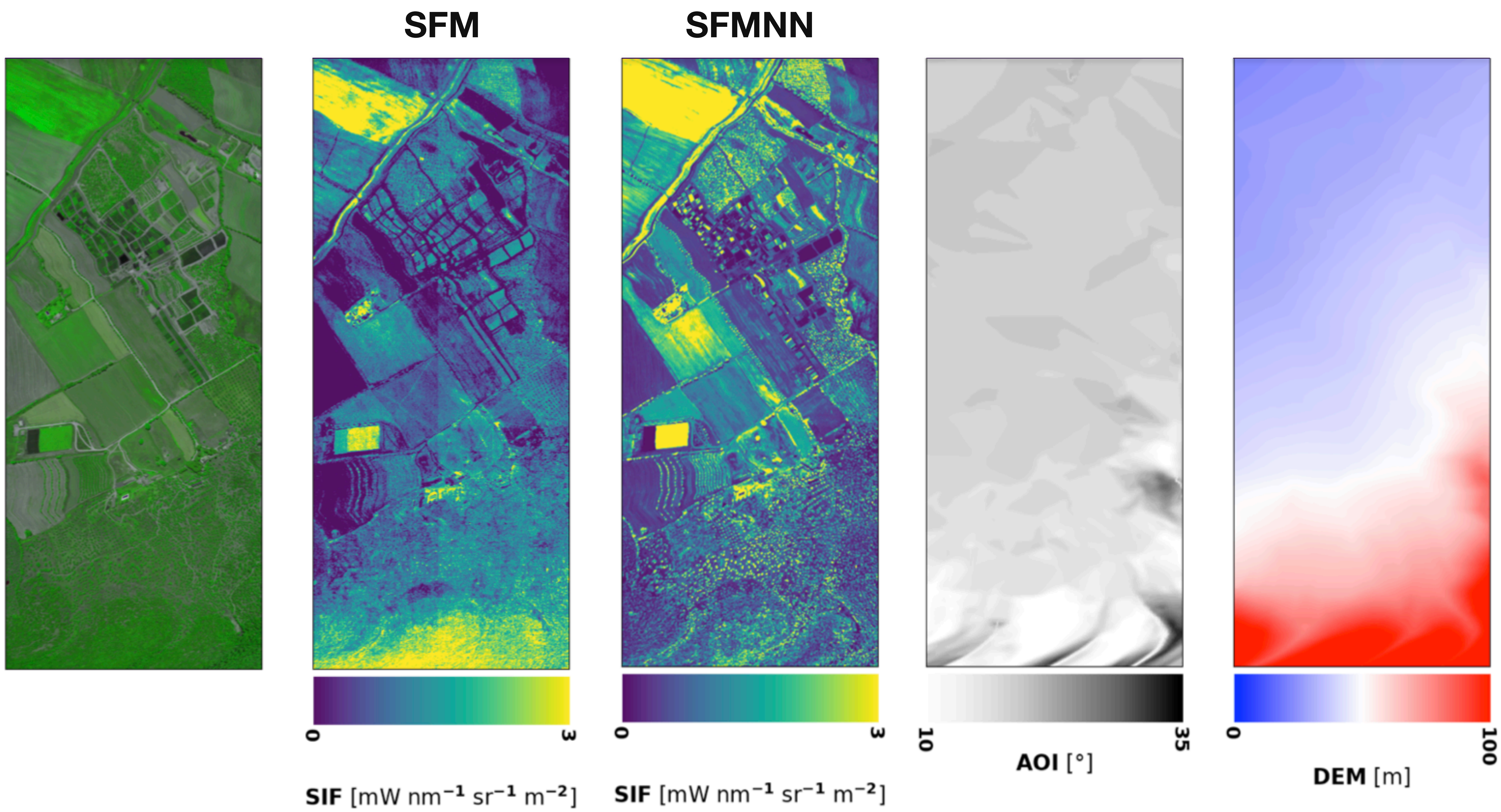
Comparison with in-situ measurements

- 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

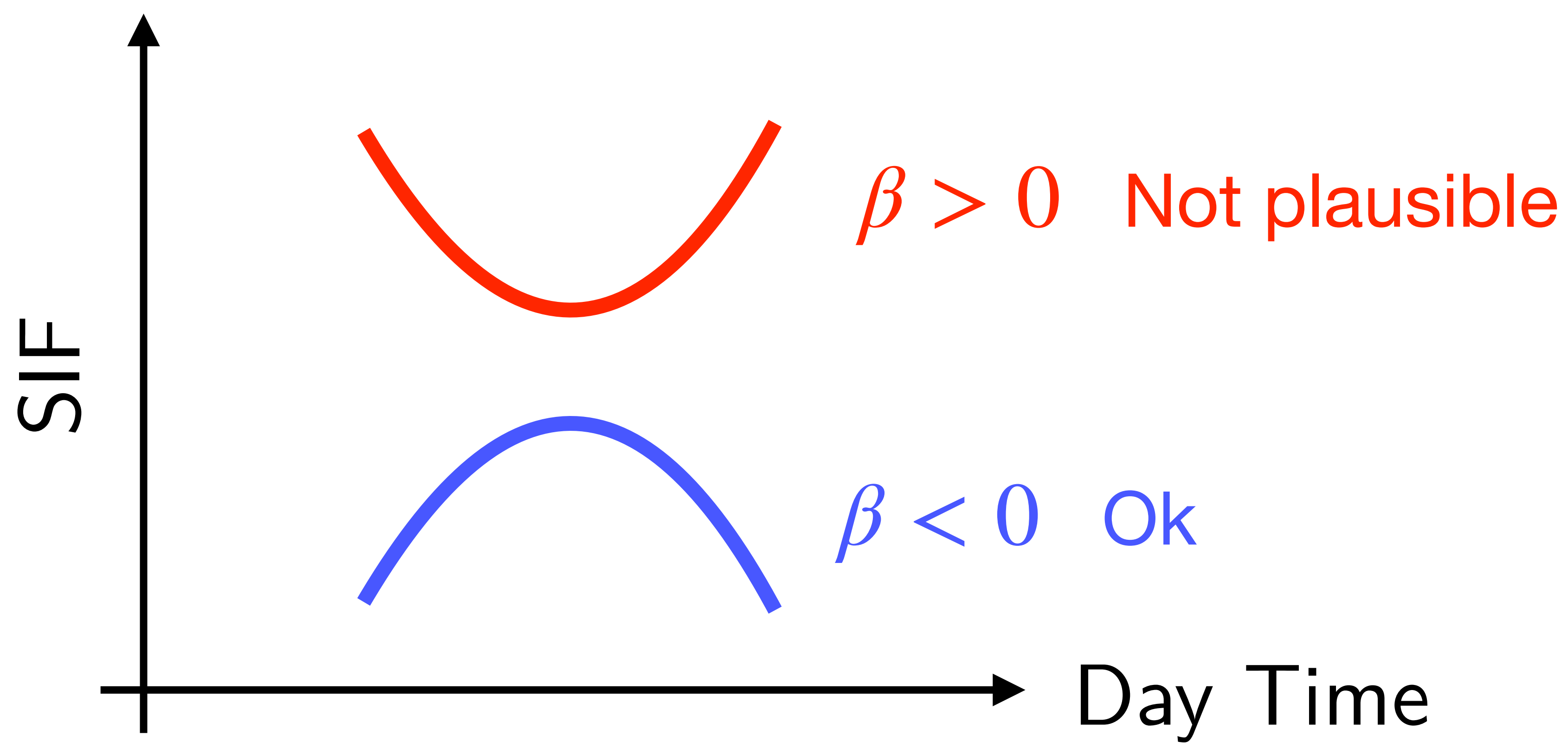
Data Set		r^{pear}	MAE mW nm^{-1}	MAE[calib] m^{-2} sr^{-1}	N
CKA-2020 (600m)	SFM	**0.85**	**0.43 ± 0.05**	0.17 ± 0.02	18
	SFMNN	0.78	0.90 ± 0.03	0.18 ± 0.04	18
	iFLD	0.53	0.41 ± 0.07	0.24 ± 0.01	18
SEL-2018 (600m)	SFM	0.91	0.53 ± 0.07	0.11 ± 0.00	12
	SFMNN	**0.93**	**0.40 ± 0.03**	0.11 ± 0.00	12
	iFLD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

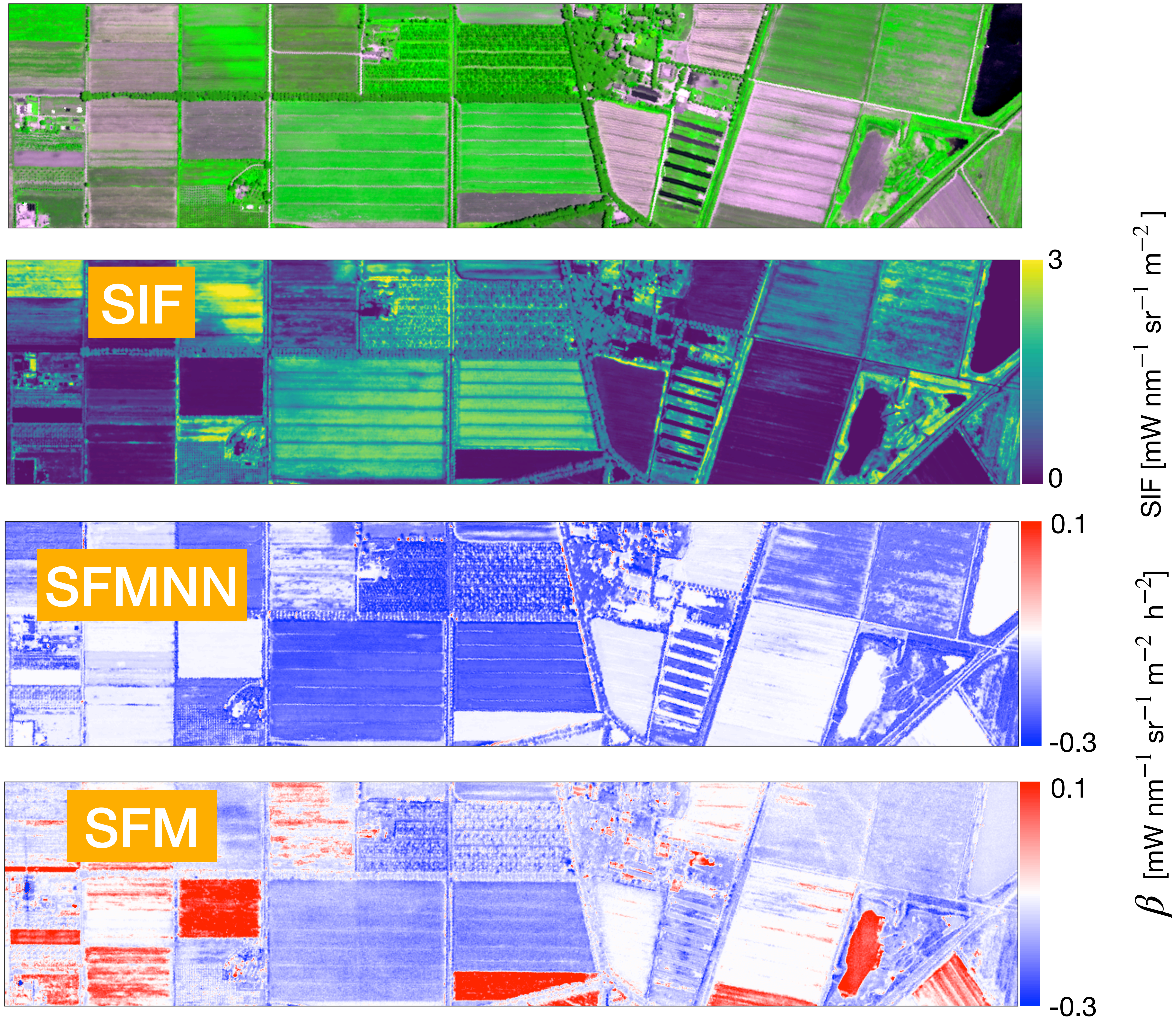
SIF Prediction in Topographically Variable Terrain



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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