Leveraging a large-scale radiative transfer simulation for an emulator based retrieval scheme of sun-induced fluorescence in HyPlant imagery

17.04.2024

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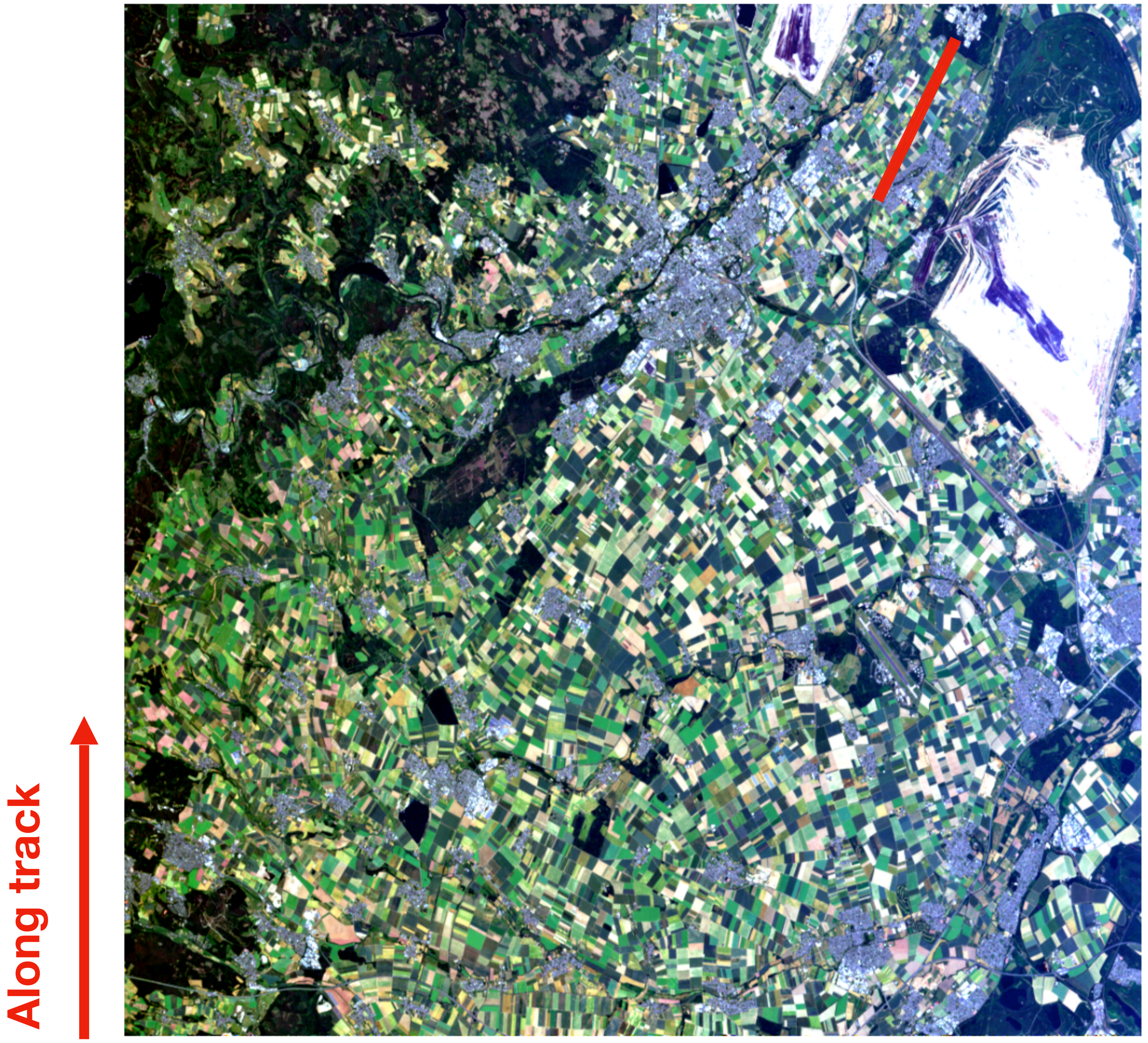
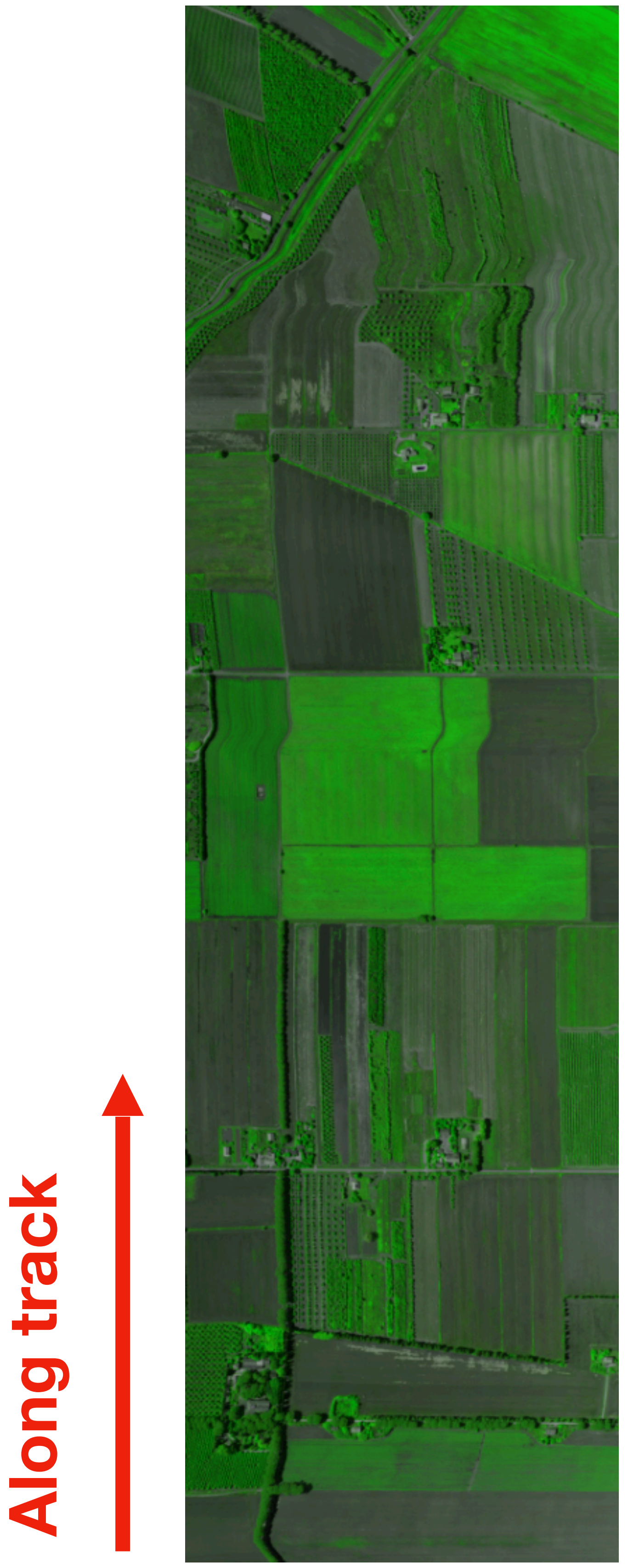
FluoMap: Sun-induced fluorescence (SIF) prediction from different imaging sensors

- SIF estimation from imagery
  - from **different sensors:** HyPlant, DESIS
  - at **multiple spatial scales (**0.5m - 2m / 30m)
- **Model development** and **intercomparison**
  - Corresponding data sets acquired in 2020 and 2023

DESIS



HyPlant FLUO



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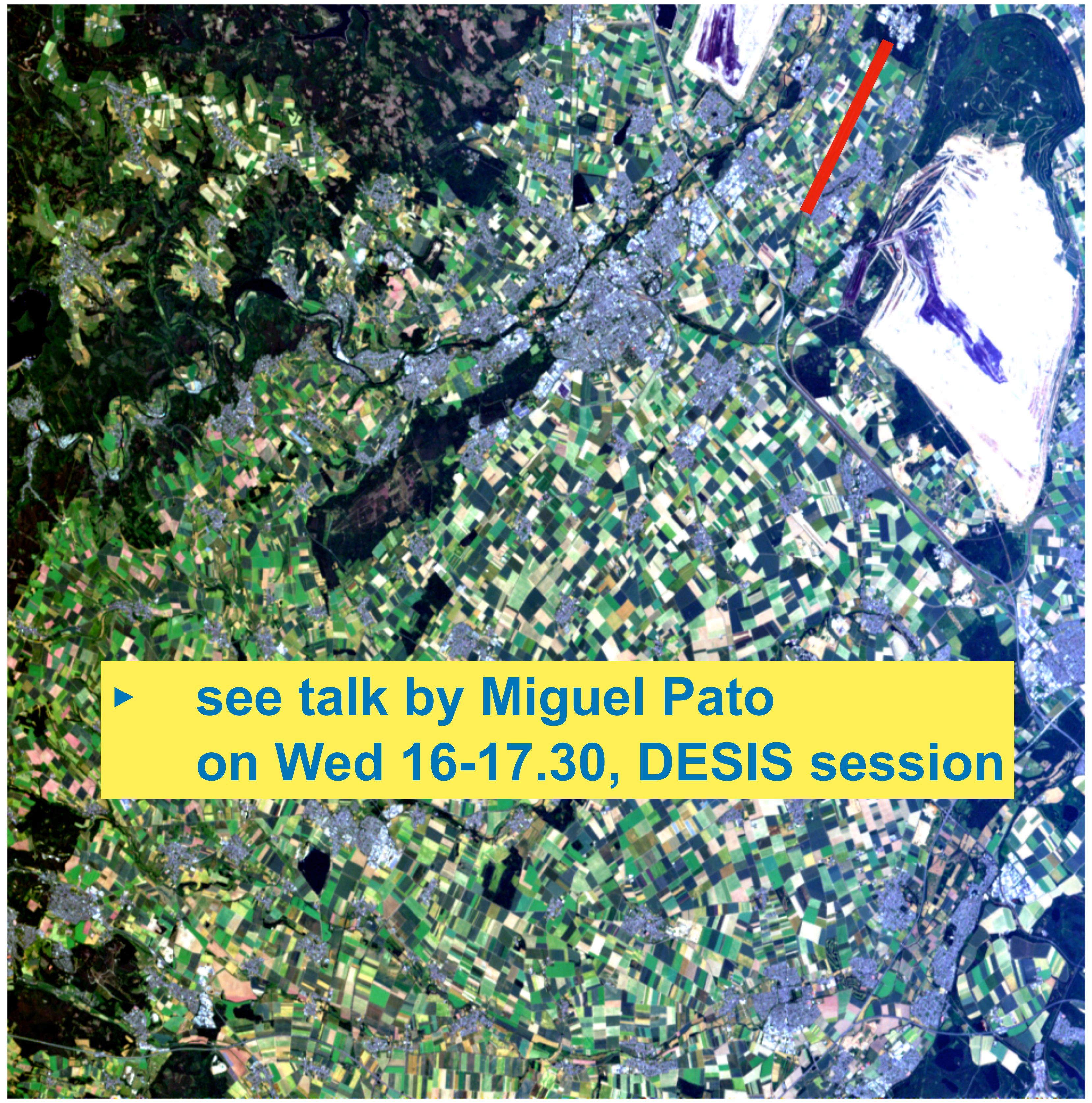
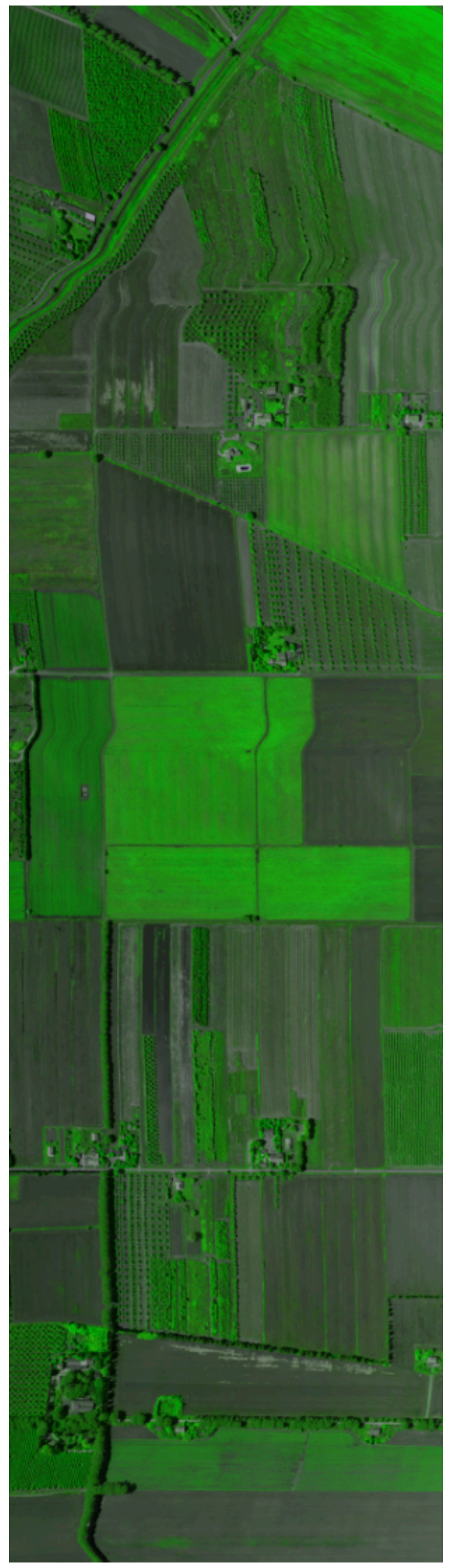


Along track

HyPlant FLUO



Along track

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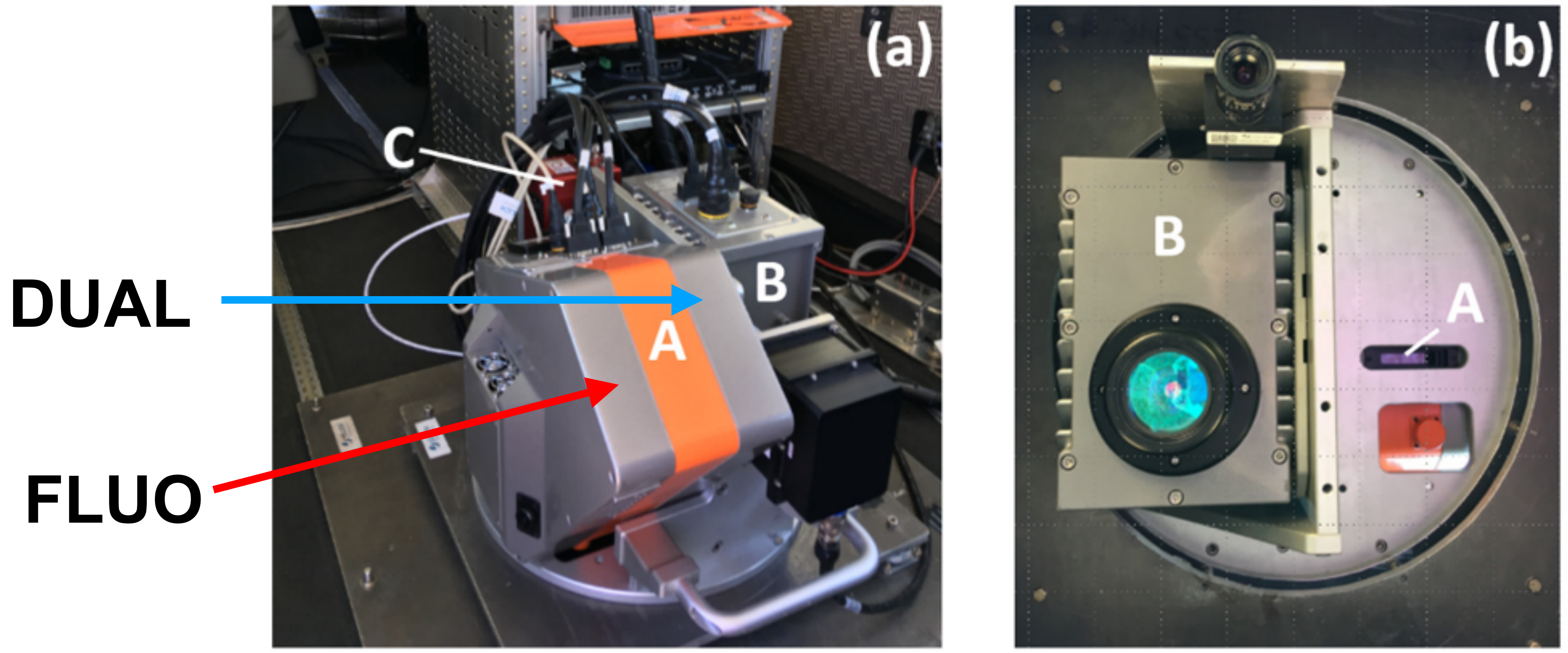
Model Development with FLEX' Airborne Demonstrator HyPlant

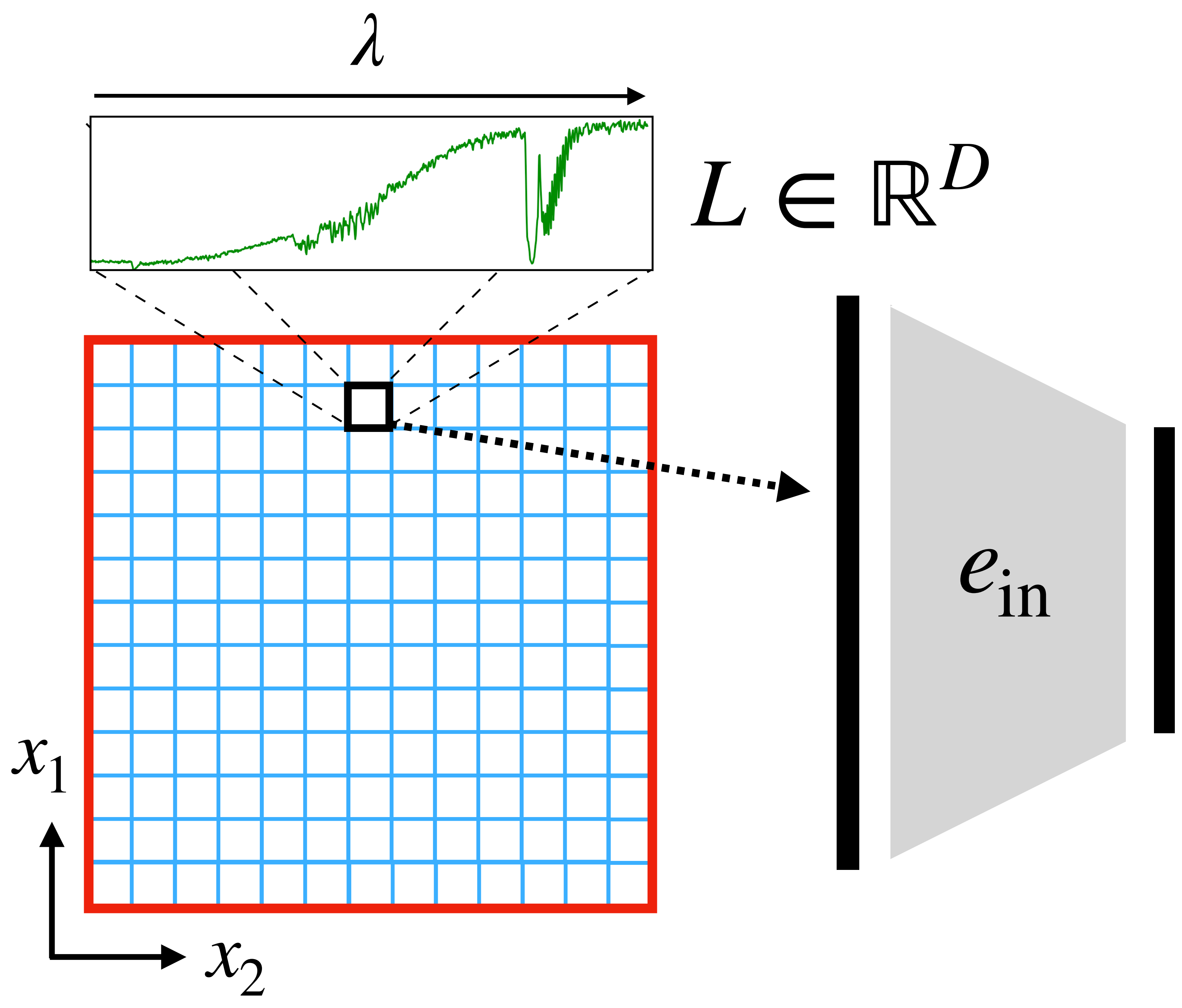
- FLUO is the **airborne demonstrator** for **FLEX**
- 0.24 nm FWHM, 0.11 nm SSI
- 6 years of comparable campaign acquisitions
- > 770 acquisitions, 384 × [2000, 10'000] px
- Operational Baseline SIF Retrieval Methods
  - *Spectral Fitting Method (SFM)*, Cogliati et al. 2019
  - *Improved Fraunhofer Line Discrimination (iFLD)*, Damm et al. 2022



We extend the Spectral Fitting Method Neural Network (SFMNN) with accurate forward simulation

[Buffat et al, IGARSS 2023](#)

Buffat et al. 2024, submitted



$$\underline{v} \in \mathbb{R}^d \longrightarrow \underline{p} \longrightarrow \hat{L}(\underline{p})$$

- Train an **encoder** e_{in} and **decode** to physical parameters $\underline{p}$
- Physical, physiological and sensor-related constraints enforced by **loss and architecture**
- **Four-stream model** $\hat{L}$ allows for self-supervised training
- Yields performance comparable to SFM (Cogliati et al. 2019)

- Leverage exact radiative transfer models (RTMs) to improve $\hat{L}$

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Strategy

Simulation
atmospheric radiative transfer
sensor model

→

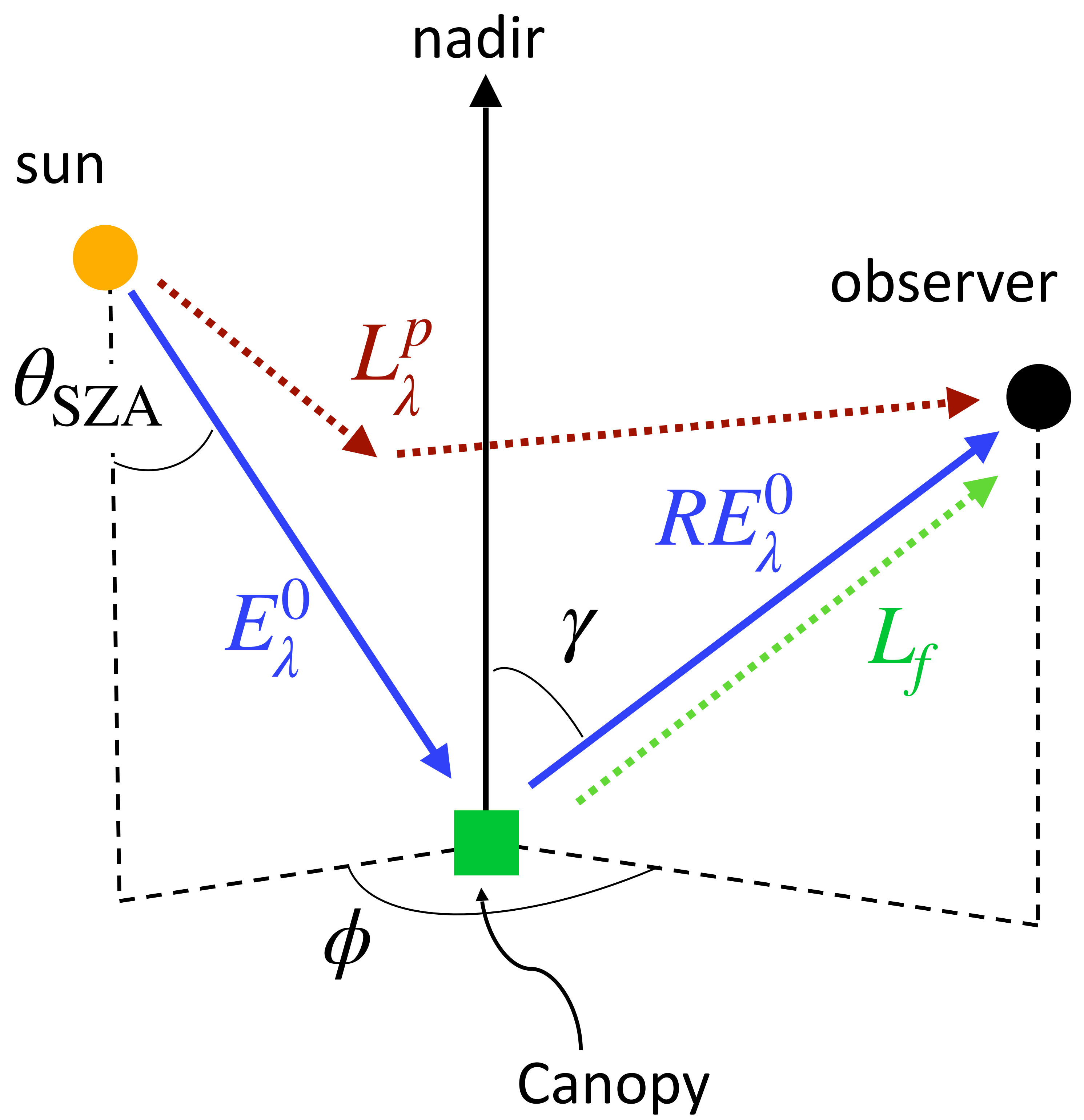
Emulation
Fast emulator for neural network training

→

Tight Emulator Integration
Integrate Emulator directly in the predictor network

↓

Self-supervised Neural Network Training
Constraint & Loss Formulation



$$L_\lambda = \left(\frac{RE_\lambda^0}{\pi} + L_f \right) T_\lambda + L_\lambda^p$$

RE_λ^0 : Reflected solar irradiance

L_f : Fluorescence Emission

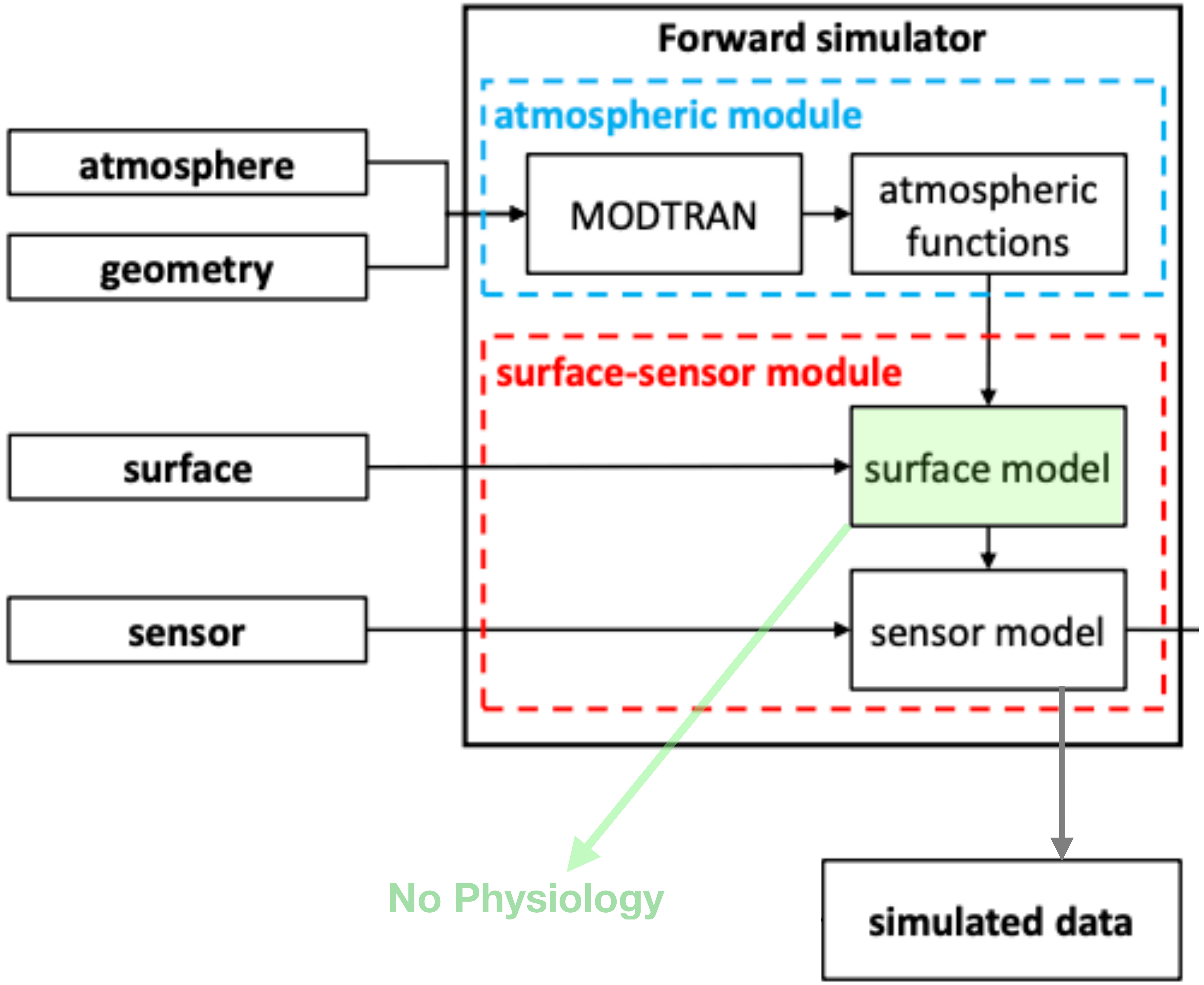
L_λ^p : Path radiance

$\theta_{\mathrm{SZA}}, \gamma, \phi$: Solar zenith, Viewing and Relative Azimuth Angle

Simulation and emulation of atmospheric radiative transfer and sensor response

- Dedicated **simulation tool** for radiances around **O_2-A** absorption band
  - Atmosphere & geometry: MODTRAN6
  - Reflectance & SIF: parametric models
- **Dense sampling** of parameter space
  $\sim 1.5 \times 10^7$ HyPlant samples
- **Emulator: 4th order polynomial** approximates the simulations very well
  - Fast computation
  - Easily integrated in a neural network

Pato et al. (2024), submitted



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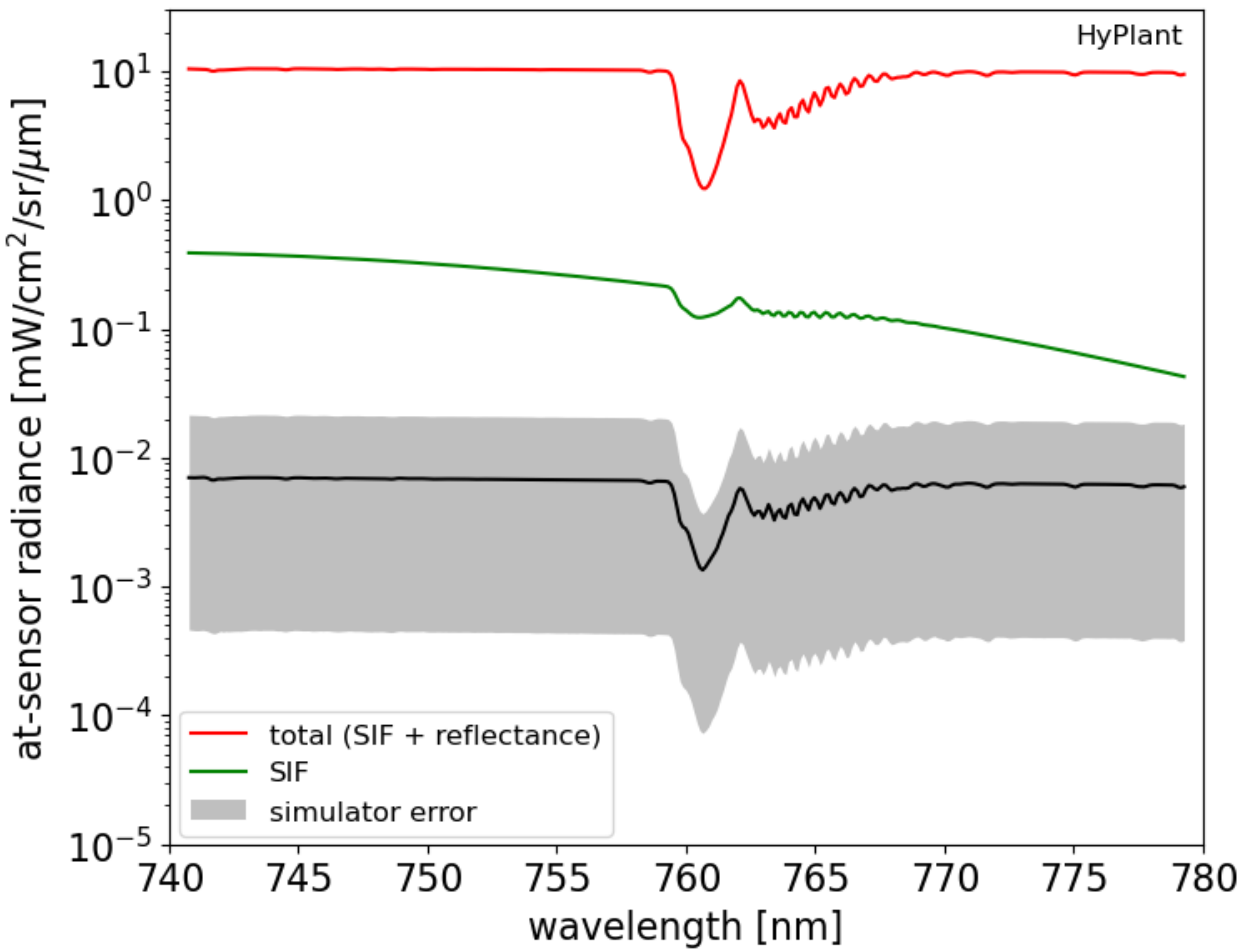
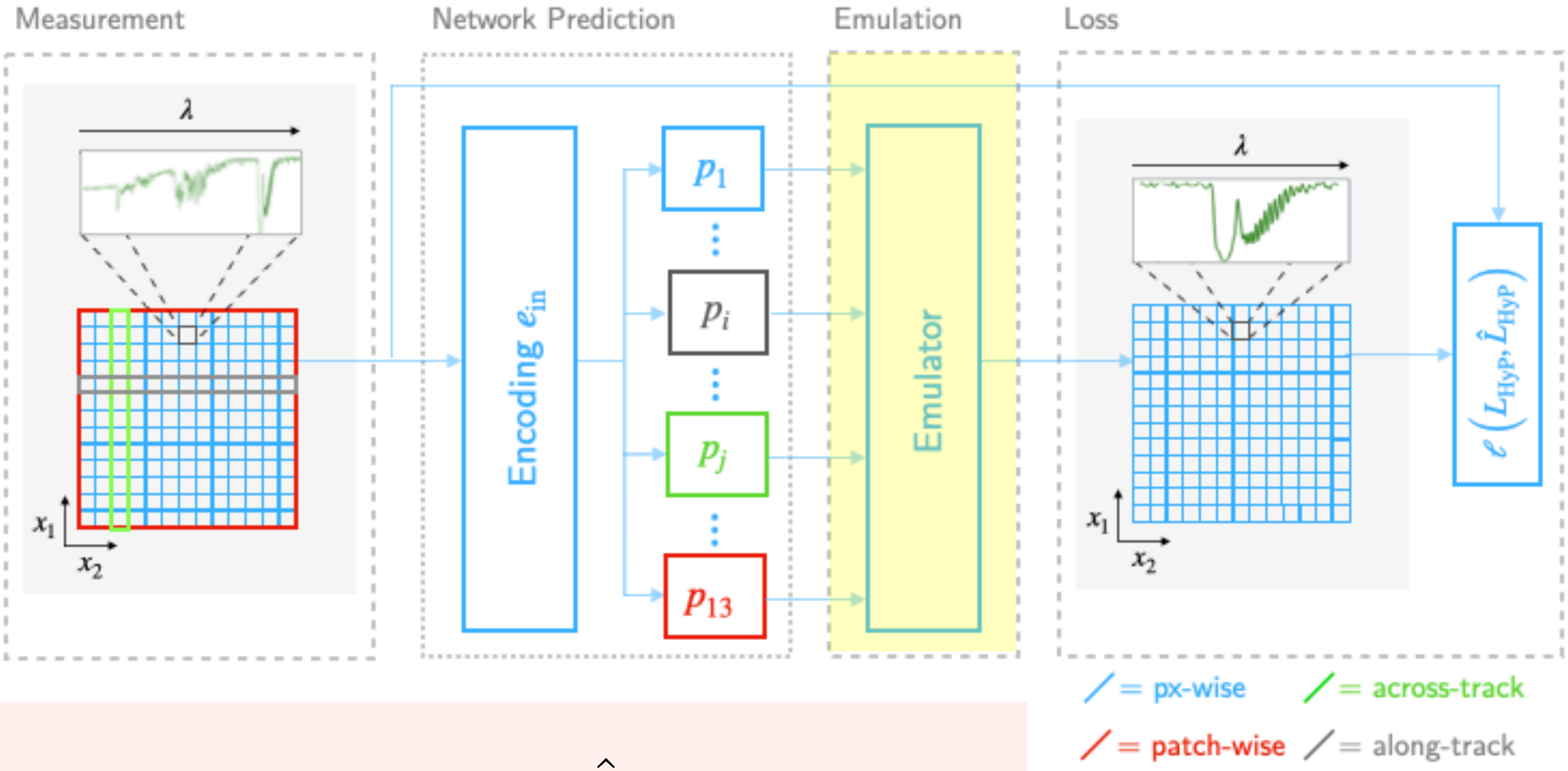


Emulator integration in a neural network architecture

- Pre-training + Fine-tuning
- Specialized **loss**
- Architectural **constraints**:
  - Pixel: Reflectance, SIF
  - Patch: Atmosphere
  - Across-Track: Sensor



$$\ell(L,\hat{L}) = (\ell_{\mathrm{MSE}} + \gamma_f\,\ell_f + \gamma_N\,\ell_{\mathrm{NDVI}})\,(L,\hat{L})$$

SNR-based weighting

Residual loss

Physiological prior

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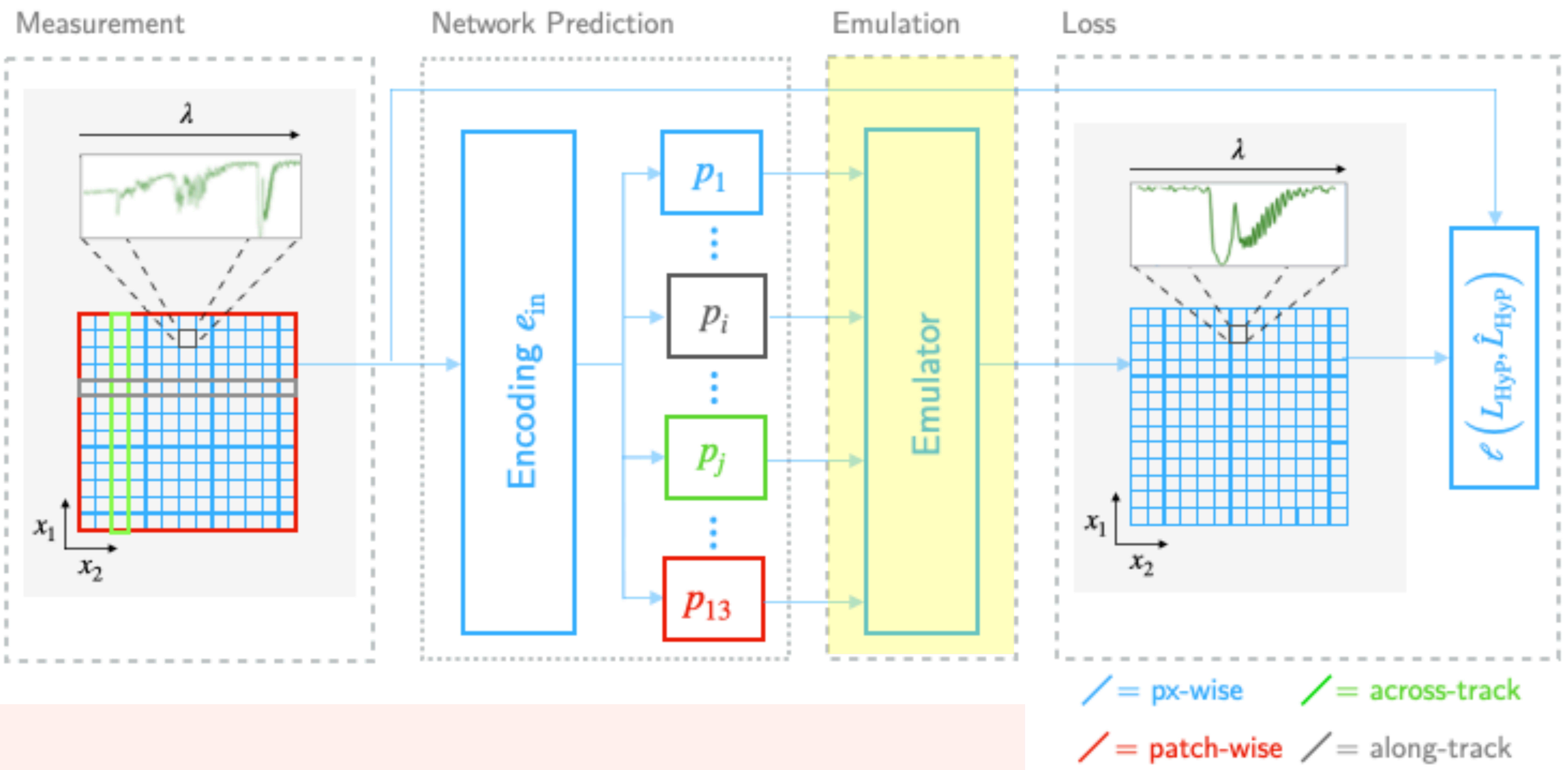

- **Benefits**
  - Upon Generalization: **fast inference**
  - Exact **pixel-wise physical parametrization**

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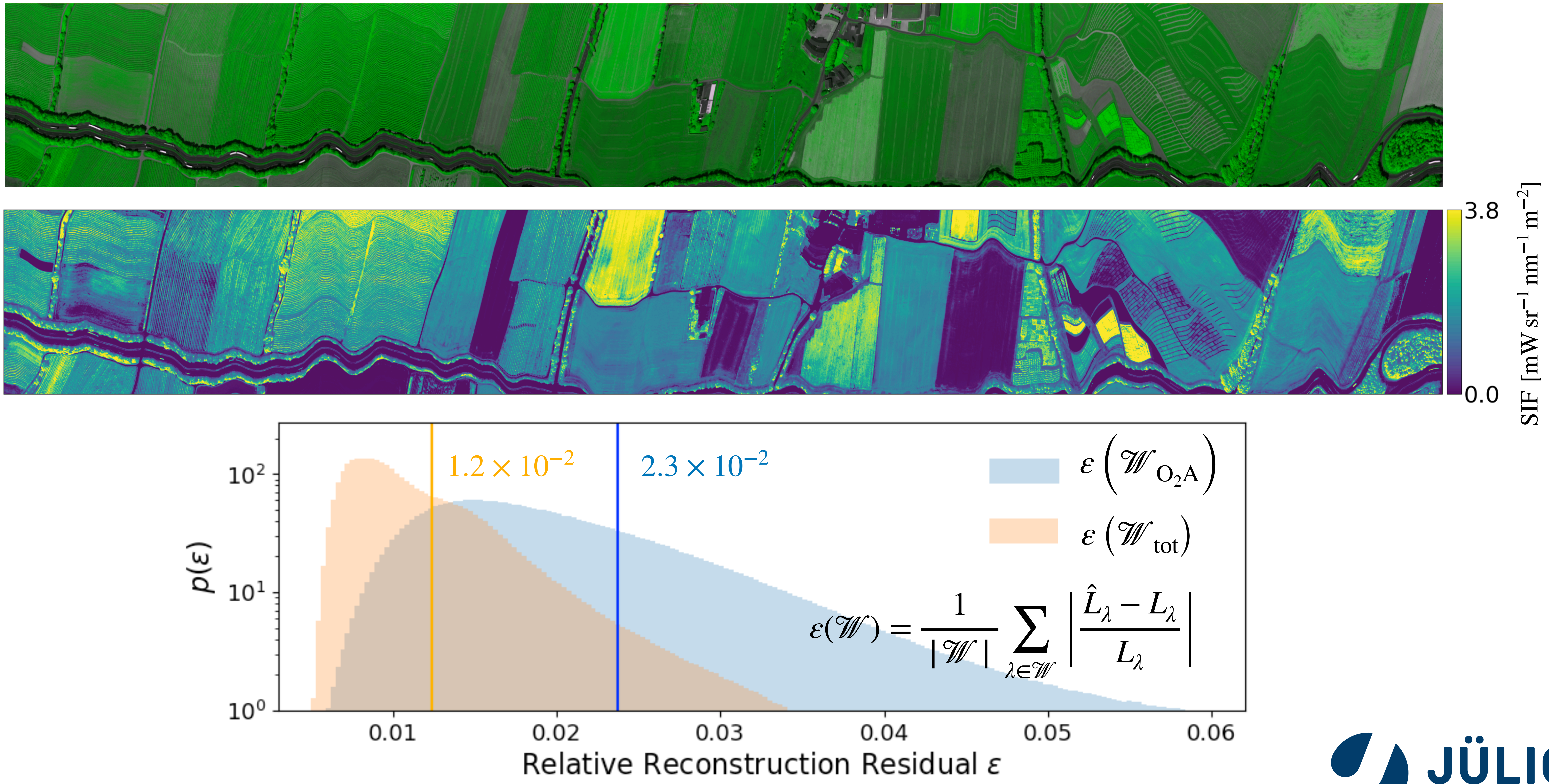
Reconstruction errors



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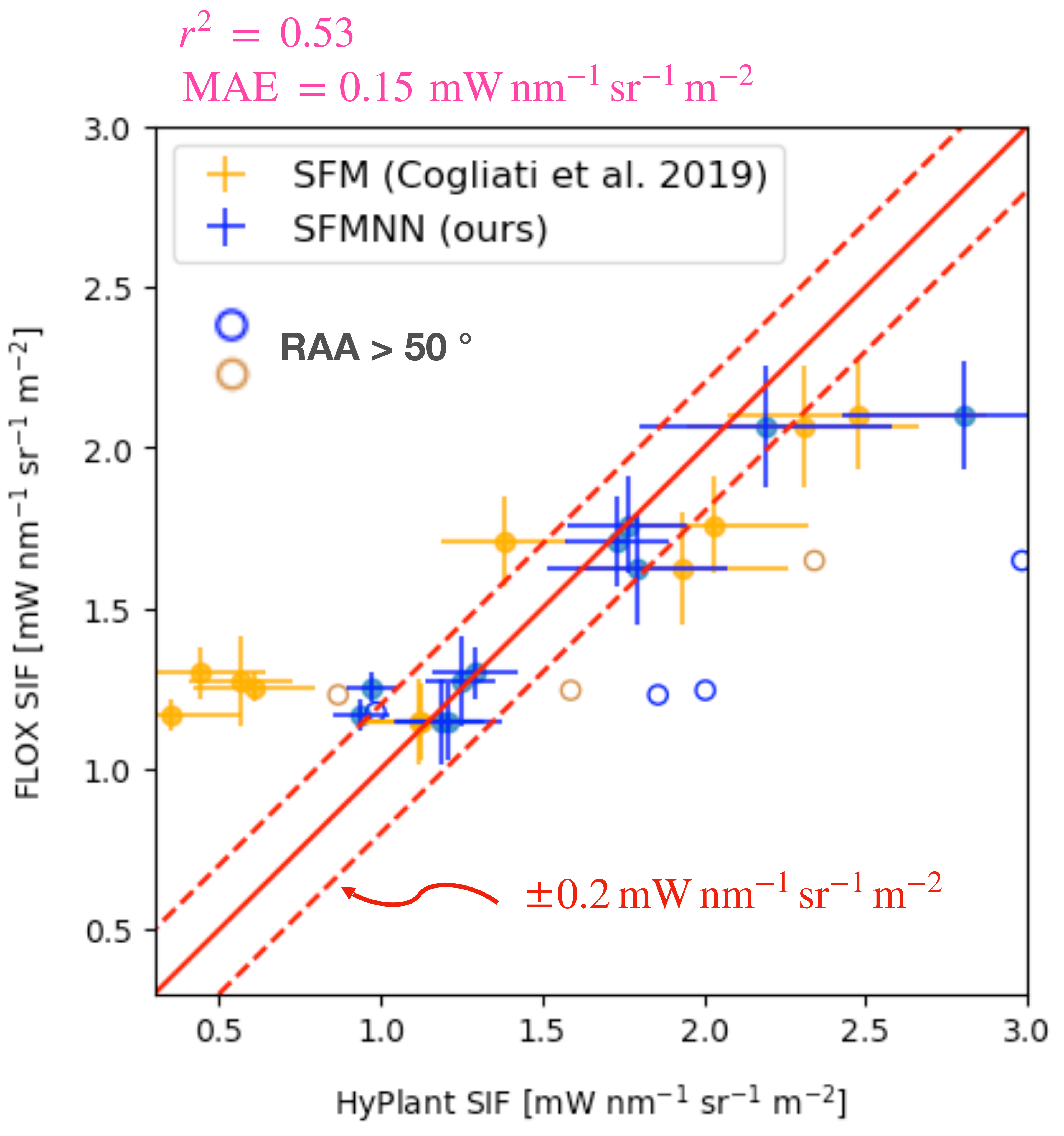
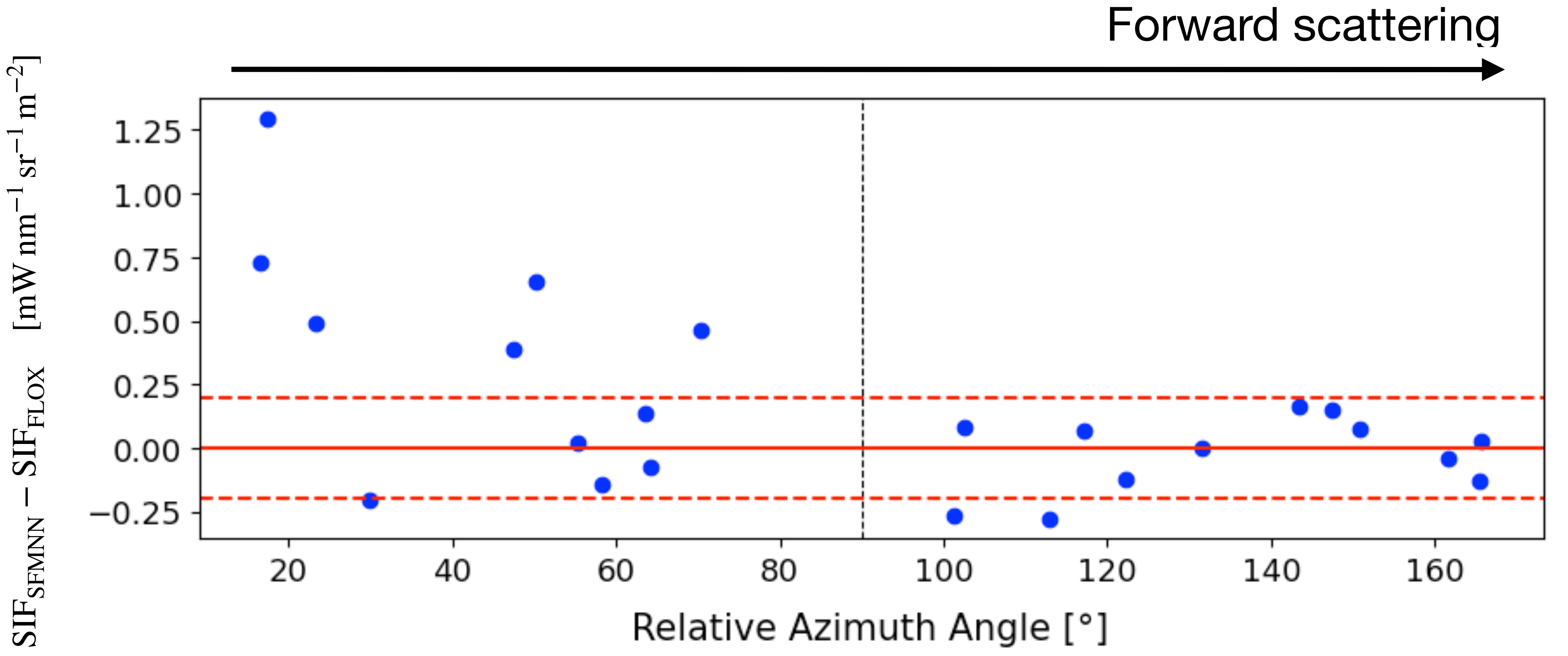
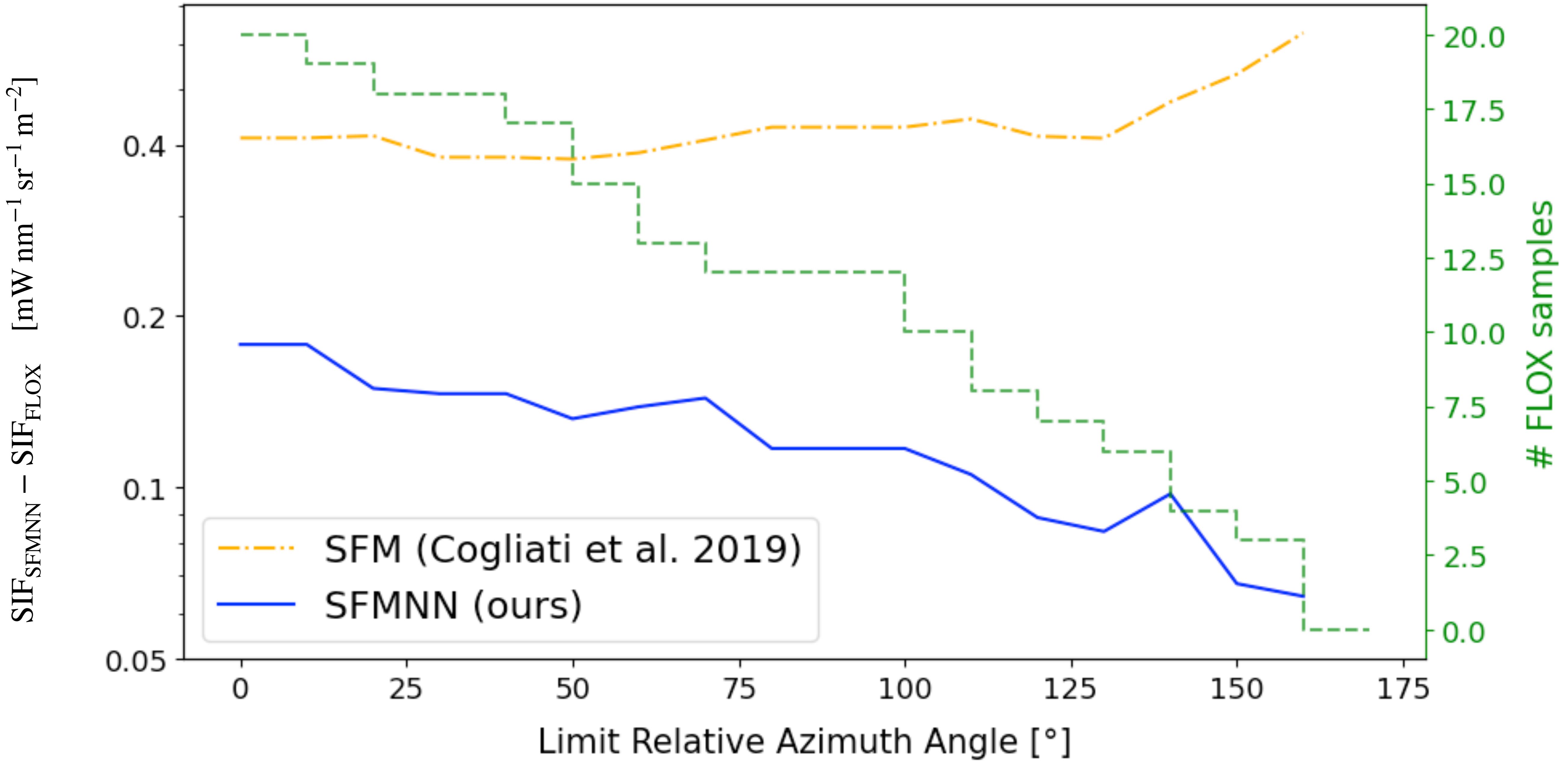
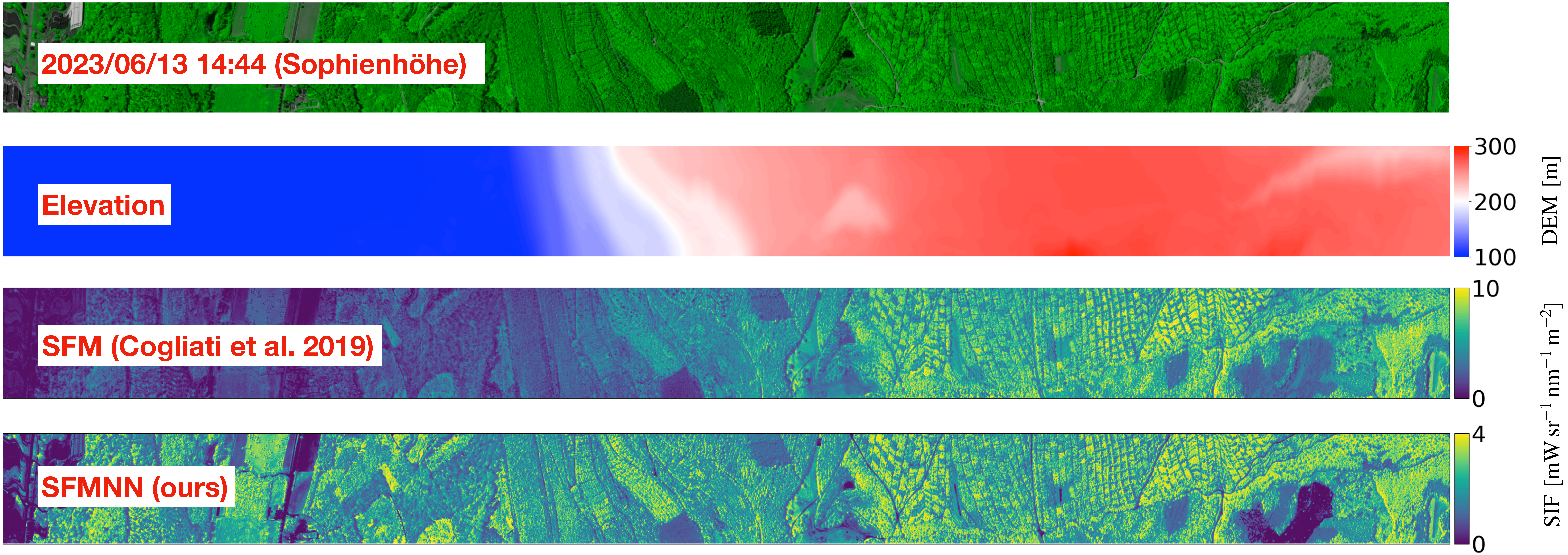
Campaign data set validation with in-situ SIF measurements in a winter wheat field







Pixel-wise parametrization allows for compensation of optical path differences in hilly terrain



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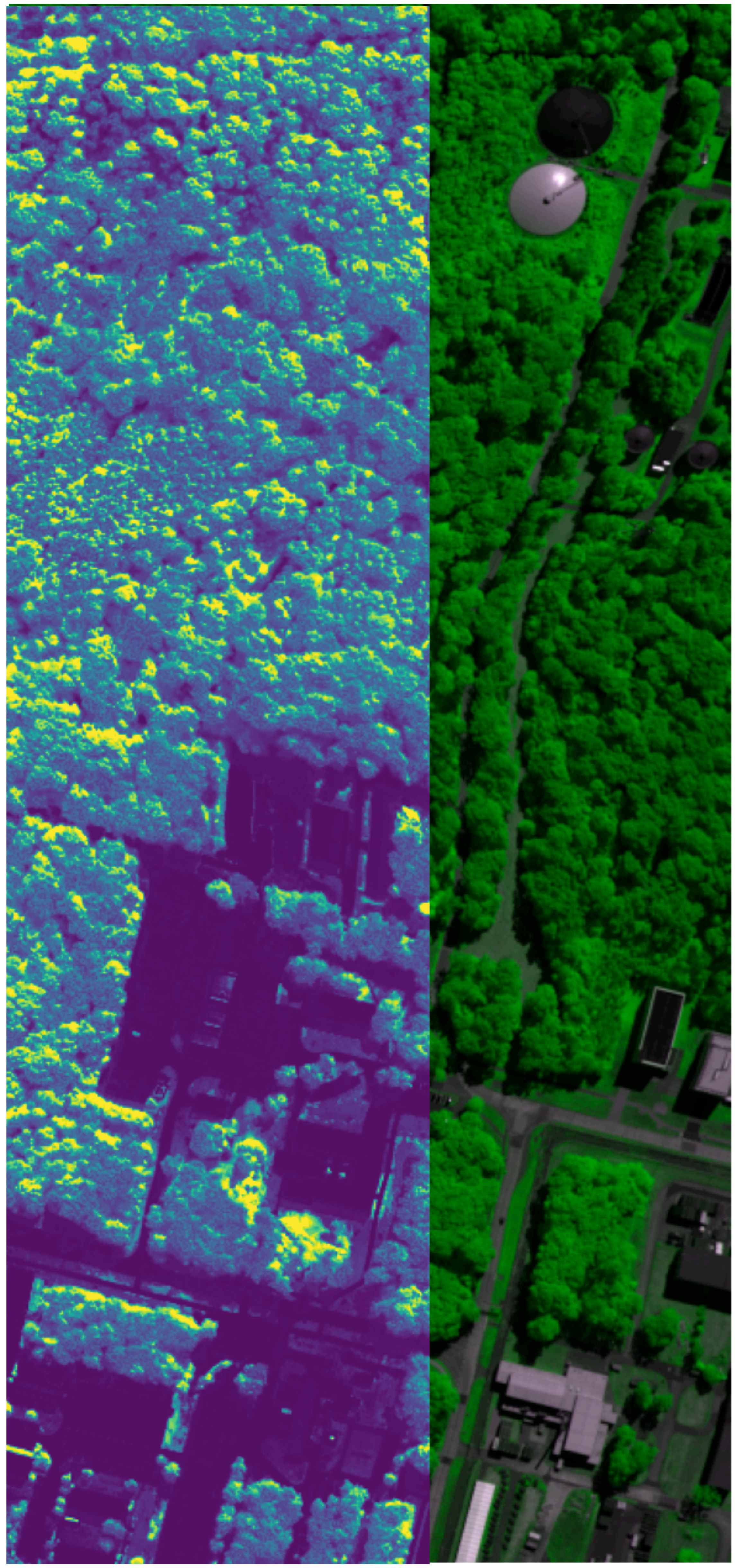
Conclusion & Outlook

- The **hybrid SIF retrieval** approach **improves SIF** predictions
  - **Extending** simulation **data base** extension for larger validation study
- **Portability to other** airborne and spaceborne **sensors**
  - DESIS (see talk by Miguel Pato on Wed 16-17.30, DESIS session)
  - FLEX
- After training, the **retrieval model is fast**
  - Optimization isn’t performed for each pixel.
  - Generalization of trained models across different domains (e.g. different campaigns) has not yet been established systematically.
- **Pixel-wise model parametrization** is possible without simplifications.
  - SIF prediction in hilly terrain can be addressed.



Acknowledgements: This work is part of the project “FluoMap” funded by the Helmholtz Initiative and Networking Fund, Helmholtz AI, Deutsches Zentrum für Luft- und Raumfahrt (DLR) and Forschungszentrum Jülich GmbH (FZJ). 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

Backup

Parametrization

		Parameter
Atmosphere	model	mls
	H_2O [cm]	0.3–3.0
	O_3 [DU]	332
	AOT_{550} []	0.02–0.30
	aerosol model	rural
	g []	–
Geometry	TA [°]	0–20
	SZA [°]	20–55
	RAA [°]	0–180
	h_{gnd} [m]	0–300
	h_{sen} [km]	0.659–0.691 agl
Surface	ρ_{740} []	0.05–0.60
	s [nm^{-1}]	0–0.012
	e []	0–1
	F_{737}/F_0	0–8
Sensor	δ_{CW} [nm]	[−0.080, +0.080]
	δ_{FWHM} [nm]	[−0.040, +0.040]