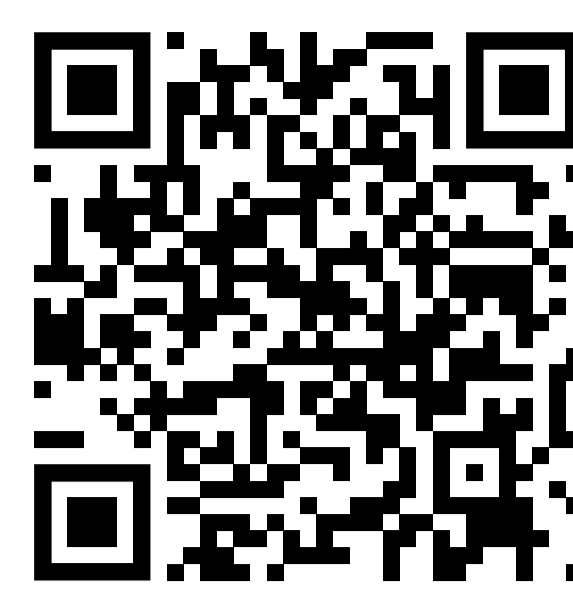
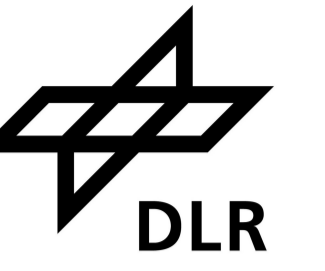


# Deep Learning Based Prediction of Sun-Induced Fluorescence from HyPlant Imagery



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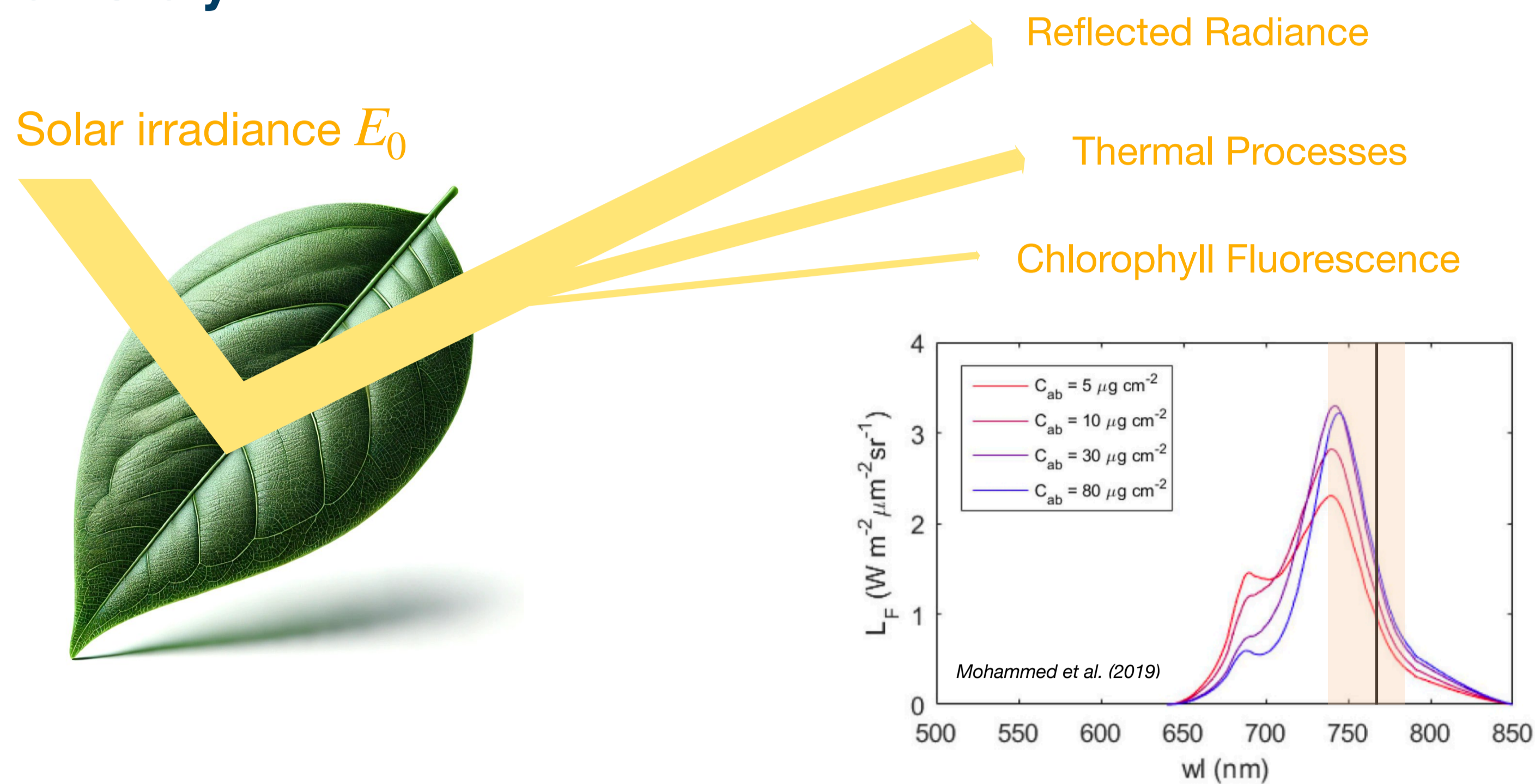
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<sup>2</sup> German Aerospace Center (DLR), Earth Observation Center, Remote Sensing Technology Institute, Oberpfaffenhofen, Germany

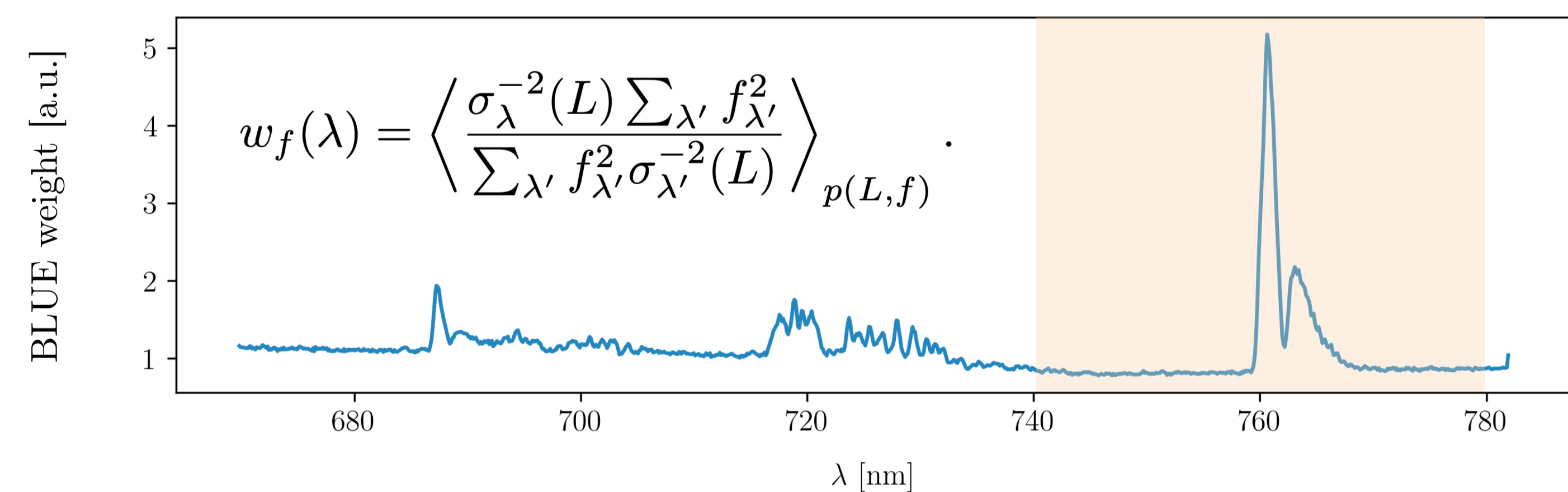
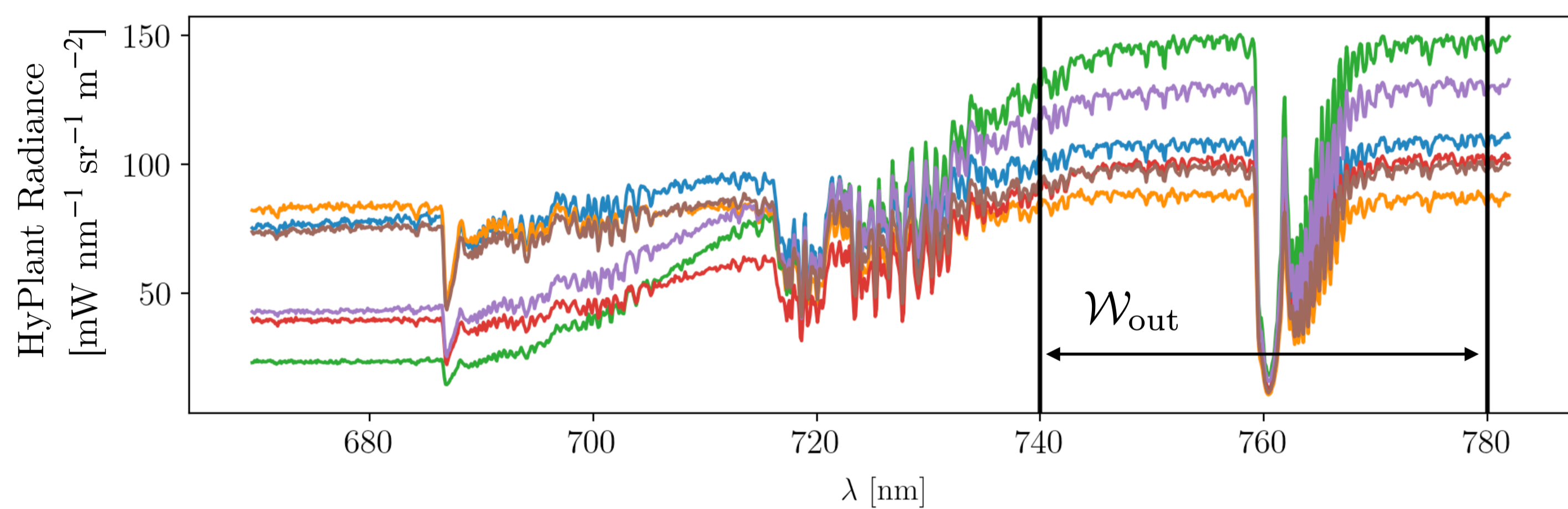
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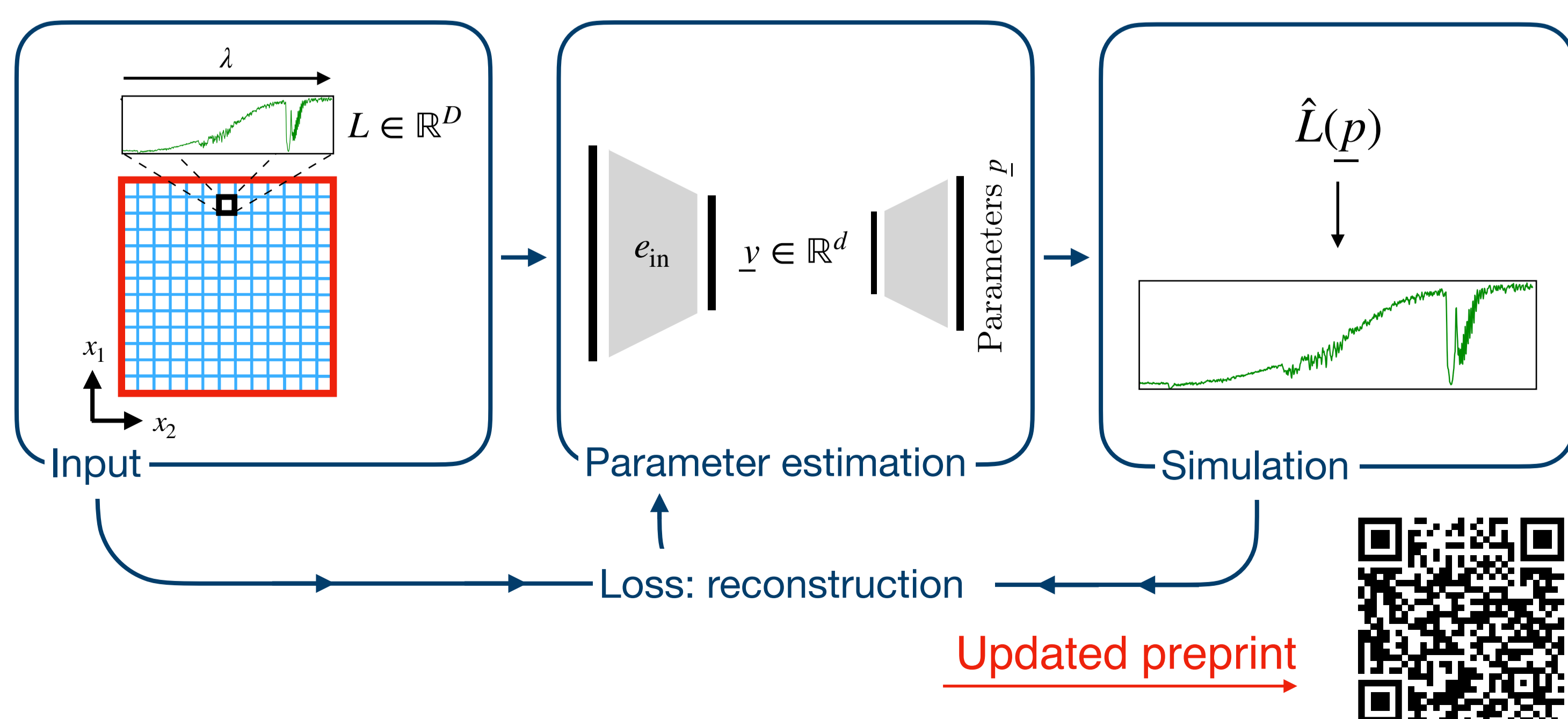
## Sun-induced fluorescence: assessing photosynthesis remotely



## HyPlant: hyperspectral imagery for SIF retrieval from airborne and spaceborne platforms



## Self-supervised training set-up



## Loss and constraints for label-free training

$$\ell(L, \hat{L}) = \left\langle \left( L_{\lambda} - \hat{L}_{\lambda} \right)^2 + \gamma_f \left( w_f(\lambda) \left( L_{\lambda} - \hat{L}_{\lambda} \right)^2 \right)_{\delta R=0} \right\rangle + \gamma_N \hat{f} \delta(\text{NDVI}_L < \tau) + \gamma_a \text{ReLU}(\hat{t}_{tot} - 1)$$

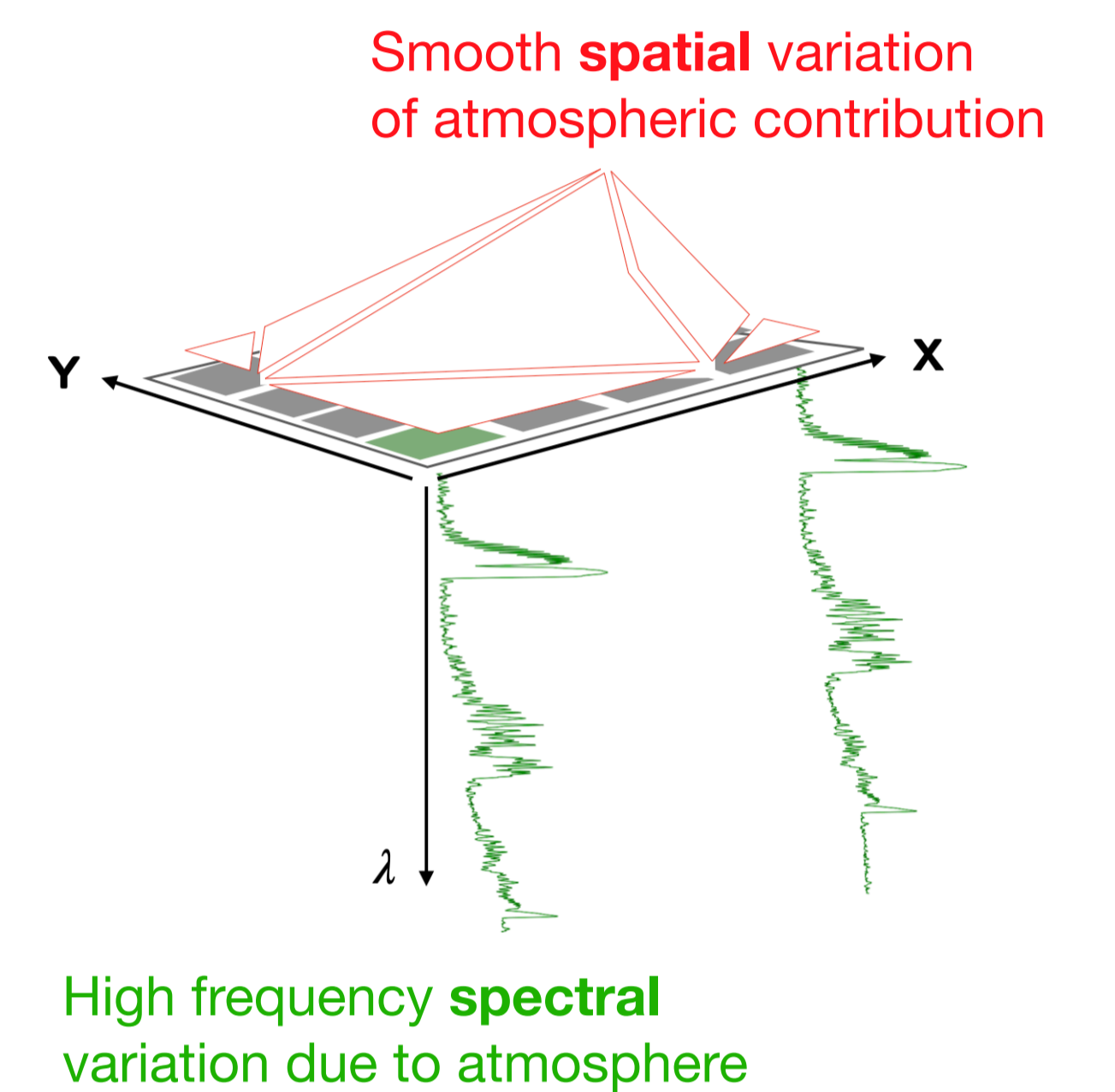


### Loss constraints

- ▶ Sensor: BLUE weighting
- ▶ Signal source: NDVI
- ▶ Physical atmosphere

### Architectural constraints:

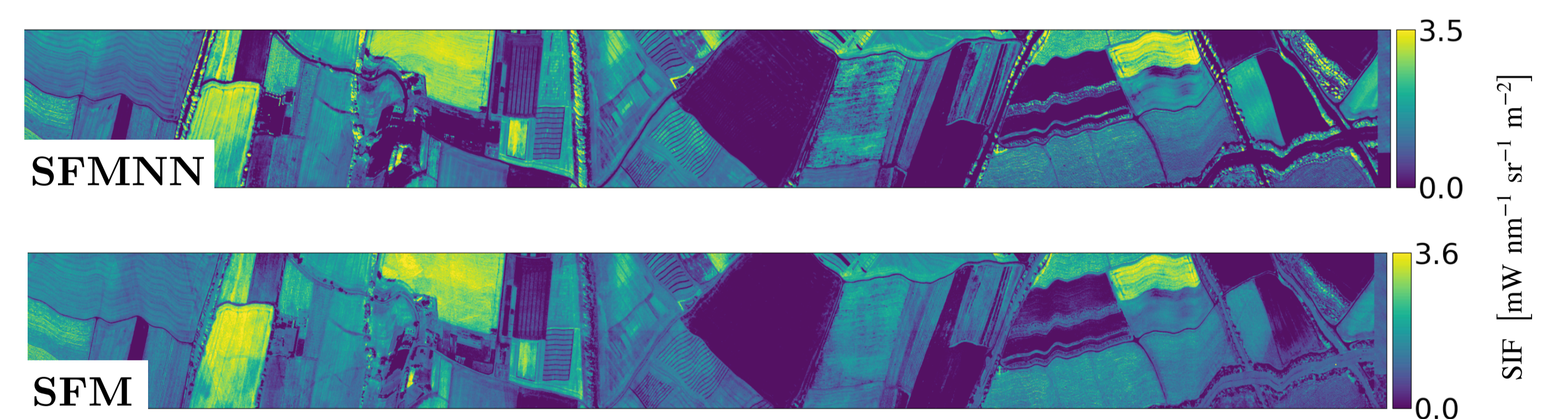
- ▶ differentiate between patch-wise and pixel-wise prediction



## Comparison with in-situ SIF measurements



Data Set		r	MAE	N
SEL-2018 (600m)	SFM	0.89	0.80 ± 0.10	11
	SFMNN	<b>0.96</b>	<b>0.68 ± 0.08</b>	11
	iFLD	0.80	<b>0.67 ± 0.08</b>	10
WST-2019 (1500m)	SFM	-0.36*	0.46 ± 0.05	22
	SFMNN	<b>0.62</b>	<b>0.19 ± 0.03</b>	22
	iFLD	-0.59	4.81 ± 0.09	22
CKA-2020 (350m)	SFM	<b>0.90</b>	0.36 ± 0.04	37
	SFMNN	0.87	<b>0.31 ± 0.04</b>	37
	iFLD	0.55	<b>0.28 ± 0.05</b>	36
CKA-2020 (600m)	SFM	<b>0.83</b>	0.42 ± 0.05	23
	SFMNN	<b>0.83</b>	<b>0.24 ± 0.05</b>	23
	iFLD	0.52	<b>0.39 ± 0.08</b>	23
CKA-2021 (350m)	SFM	0.64*	0.44 ± 0.07	7
	SFMNN	0.82	0.49 ± 0.08	7
	iFLD	<b>0.87</b>	<b>0.12 ± 0.15</b>	7
CKA-2022 (350m)	SFM	0.57*	<b>0.39 ± 0.13</b>	6
	SFMNN	<b>0.69*</b>	<b>0.33 ± 0.16</b>	6
	iFLD	-0.88*	1.13 ± 0.21	4
GLO-2021 (1150m)	SFM	0.89	<b>0.24 ± 0.09</b>	6
	SFMNN	<b>0.92</b>	<b>0.28 ± 0.14</b>	6
	iFLD	0.81*	0.74 ± 0.16	5



## Outlook

- Improved simulation  $\hat{L}$  with RTM emulation
- Applied approach to spaceborne DESIS
- Adapting for use with ESA's coming FLEX

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[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>