DEEP LEARNING BASED PREDICTION OF SUN-INDUCED FLUORESCENCE FROM HYPLANT IMAGERY

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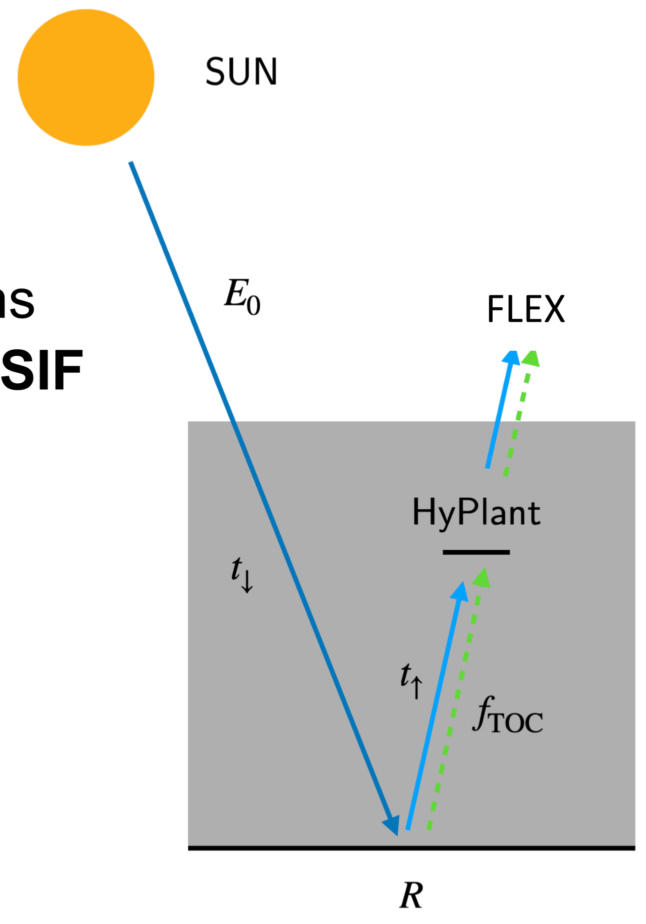
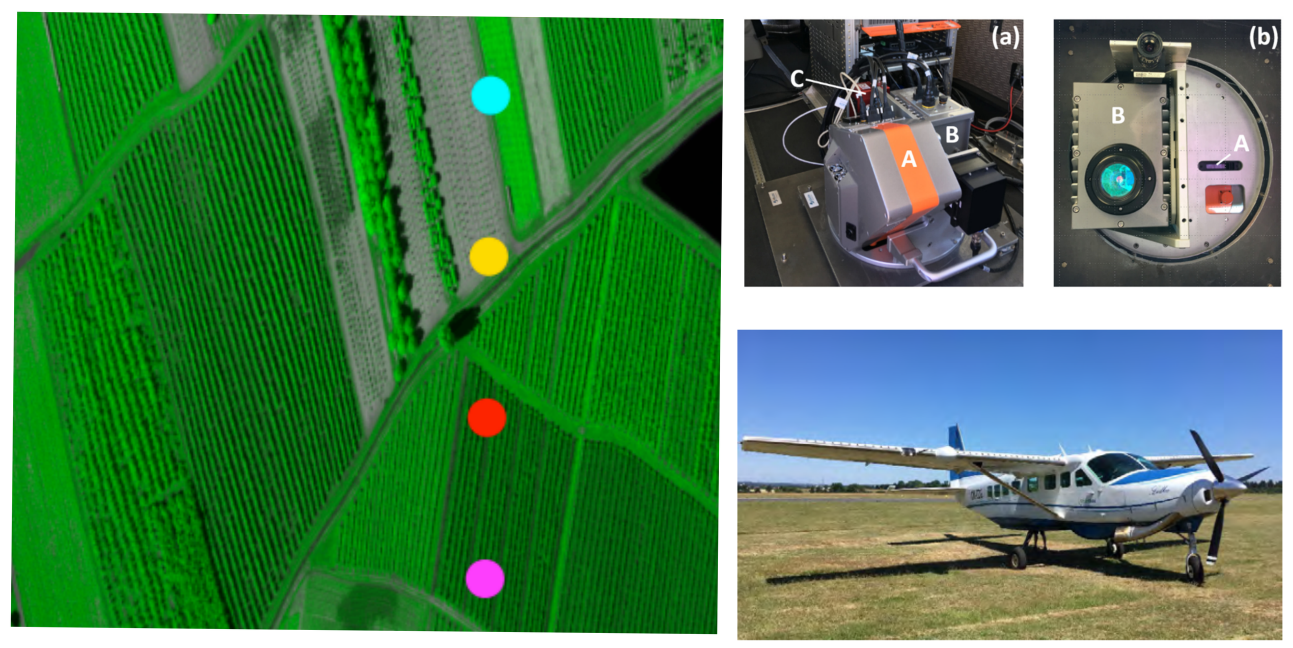
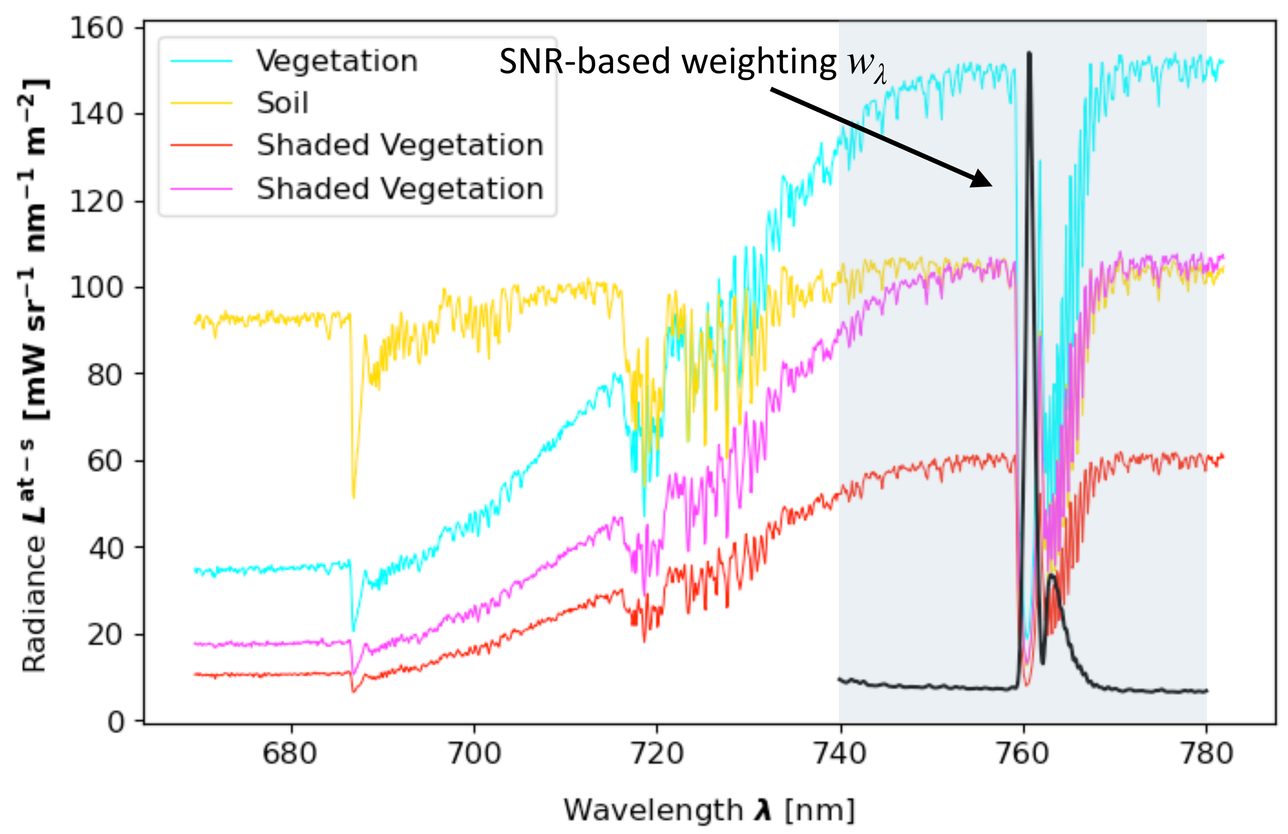
Sun-induced fluorescence is a by-product of photosynthesis

- **Plants** emit sun-induced fluorescence (SIF)
- Wide range of applications benefitting from **passive SIF estimations**
- **Emission is very weak** i.e. ~ 5% of total signal in O_2-A absorption band
- HyPlant is the airborne demonstrator for **FLEX**

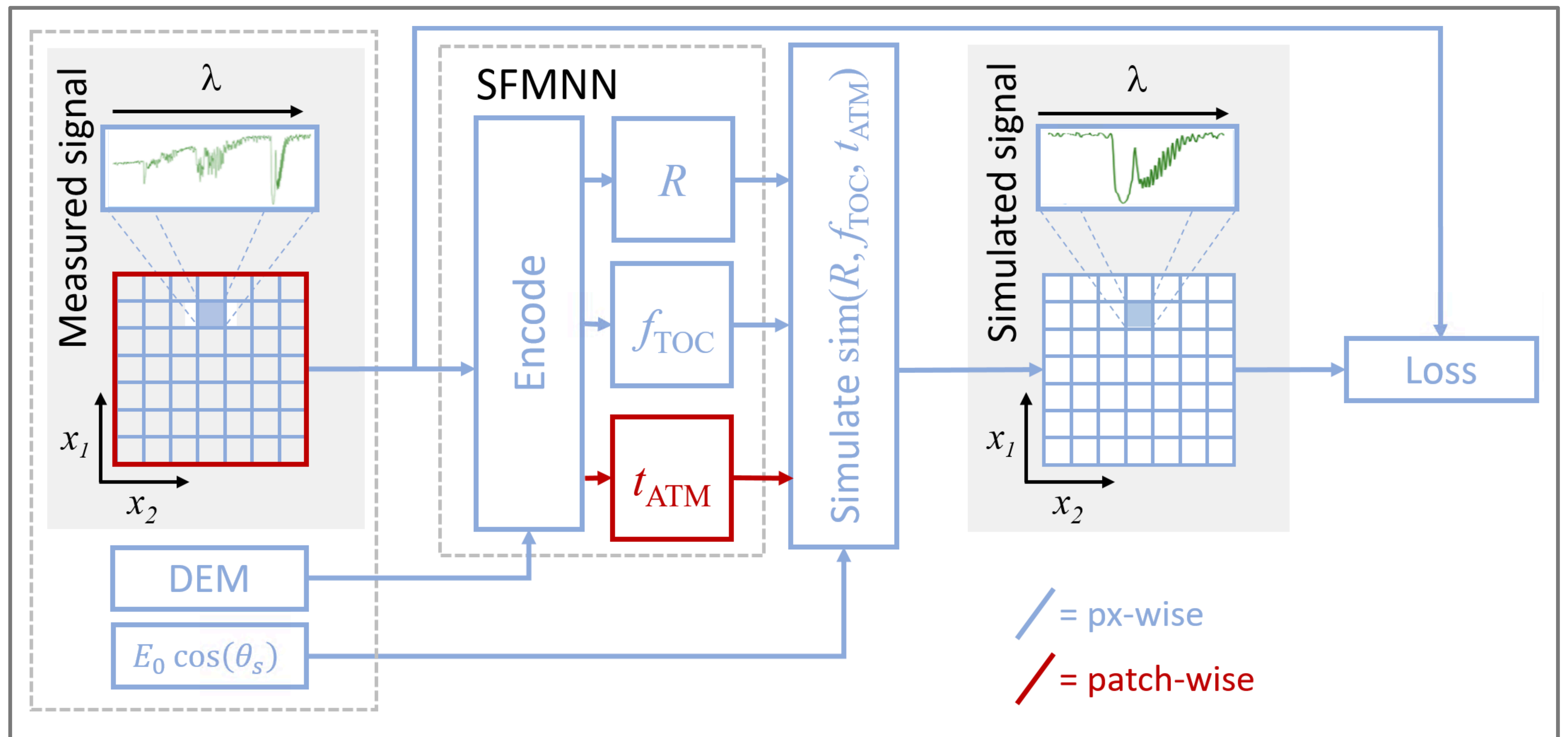


HyPlant: hyperspectral airborne spectrometer





Spectral Fitting Method Neural Network (SFMNN)



Overall residual | SNR weighting | Physiological constraint | Physical constraint

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

$$= \left\langle (y(\lambda) - \hat{y}(\lambda))^2 + \gamma_f \left(w_\lambda \, (y(\lambda) - \hat{y}(\lambda))^2 \right)_{\delta R=0} \right\rangle_{\lambda \in \mathcal{W}} + \gamma_N \, \hat{f} \, \delta\,(\mathrm{NDVI}_y \leq t) + \gamma_a \, \mathrm{ReLU}(\hat{t}_{\mathrm{tot}} - 1)$$

- Self-supervised loss evaluating residuals and additional regularizers
- Weighting boosts loss in spectral regions with high SNR of SIF signal
- Pixel-wise and patch-wise estimation as architectural constraint for surface and atmospheric parameters

Ground Measurement Validation

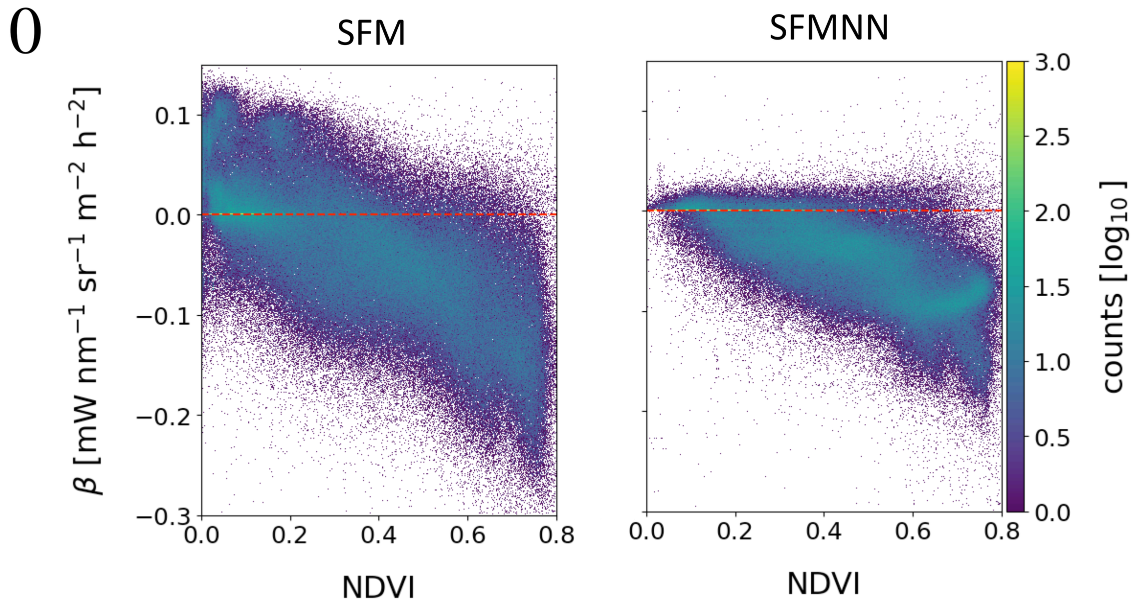
- On-par relative prediction performance, calibration is needed for absolute predictions
- Baseline Methods:
  - *Spectral Fitting Method (SFM)* Cogliati et al. 2019
  - *Improved Fraunhofer Line Discrimination (iFLD)* Damm et al. 2022

Data Set		r^{pear}	r_c^{pear}	R^2	R_c^2	MAE	MAE_c	N
SEL 2018	SFM	0.91		0.83		0.87		10
	SFMNN	**0.96**	0.95	**0.91**	**0.91**	**0.62**	0.71	10
	iFLD	0.81		0.65		0.65		10
WST 2019	SFM	-0.47		0.22		0.53		21
	SFMNN	**0.51**	-0.18*	0.26	0.03	0.81	**0.44**	21
	iFLD	-0.63		**0.39**		4.88		21
GLO 2021	SFM	**0.98**		**0.97**		0.34		5
	SFMNN	0.95	0.97	0.91	0.92	0.50	**0.12**	5
	iFLD	0.88		0.77		0.79		5
CKA 2022	SFM	0.63*		0.39		**0.38**		6
	SFMNN	0.76*	**0.84**	0.57	**0.69**	0.51	0.40	6
	iFLD	-0.63*		-2.10		1.17		4

Table 2: FLOX derived SIF measurements compared to SFMNN, SFM and iFLD SIF predictions. r_{pear} maked with * have $p > 0.05$. MAE is given in units of mW nm^{-1}m^{-2} sr^{-1}.

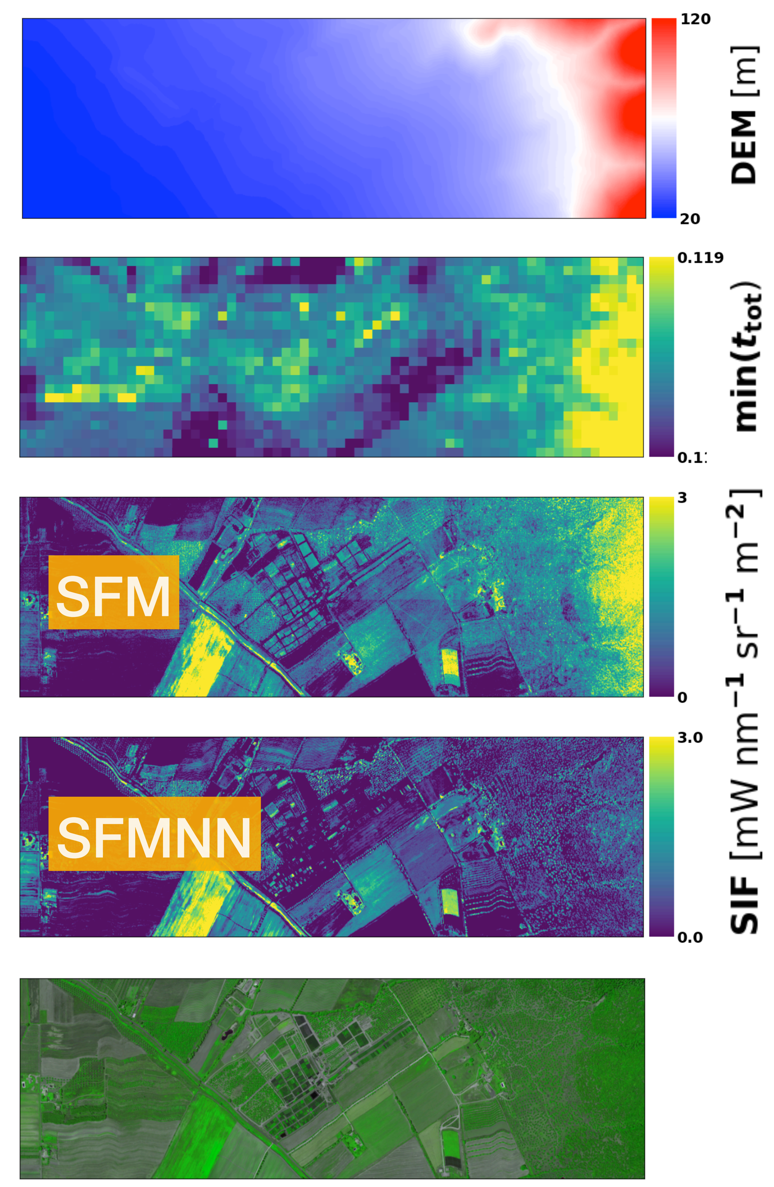
Diurnal SIF Dynamics

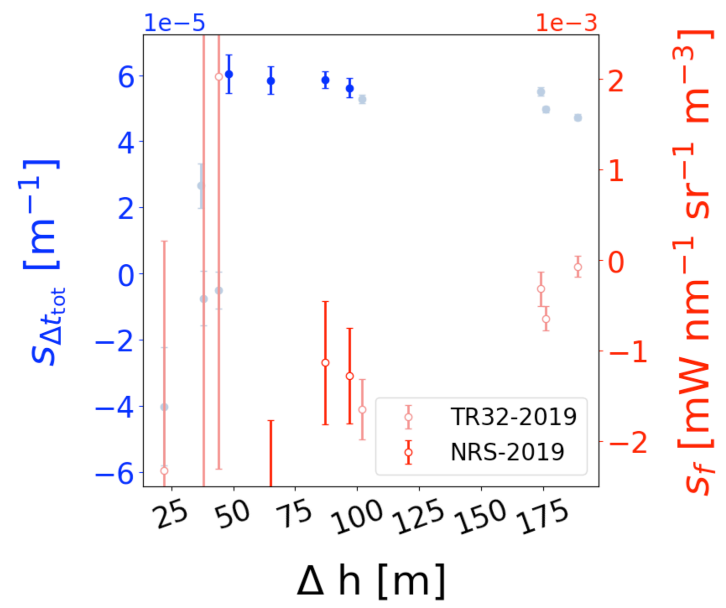
- Check for physiological plausibility: second order derivative of a time series $\beta < 0$
- SFMNN respects this constraint in pixels with low vegetative cover



SIF prediction under topographic variation

- Local atmosphere estimation allows application in complex terrain.
- Physically plausible O_2-A band depth prediction on hill slope
- General trend: slopes of O_2-A band depth and SIF are constant / vanishing





Conclusion & Outlook

- SFMNN performs well w.r.t. ground validation data, is physiologically plausible and can be applied in topographically variable terrain.

- Replace forward simulation sim with an emulator
- Apply principle to two other hyperspectral sensors:
  - FLEX, simulated imagery
  - DESIS (onboard ISS) in FluoMap project

see here

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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

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