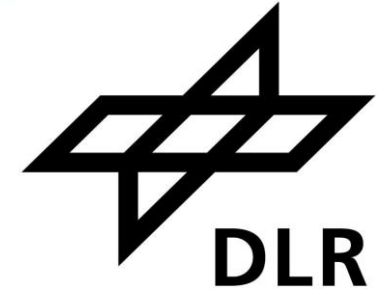


# Fernerkundung von Treibhausgas- punktquellen – Emissionsbestimmung durch Maschinelles Lernen



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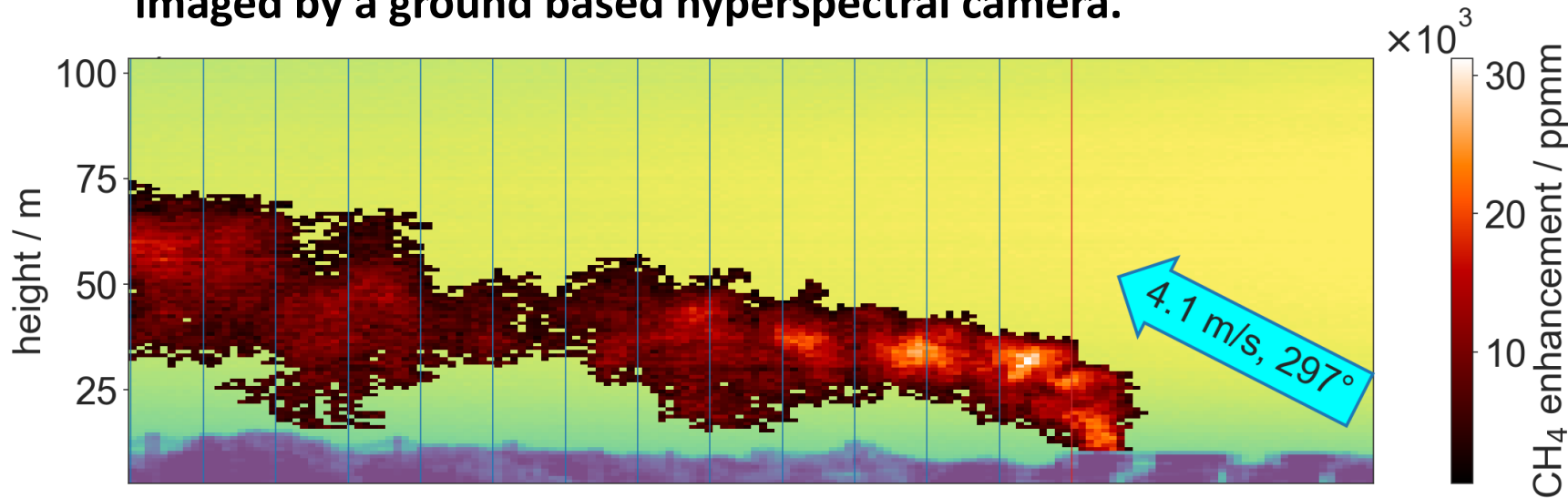
André Butz<sup>1</sup>, **Julia Marshall**<sup>2</sup>, **Thomas Plewa**<sup>1,2</sup>, Marvin Knapp<sup>1</sup>, Leon Scheidweiler<sup>1</sup>, Ida Jandl<sup>1</sup>, Theo Glauch<sup>1,2</sup>, Anna Sommani<sup>1</sup>, Sanam Vardag<sup>1</sup>

<sup>1</sup>Institute of Environmental Physics, Heidelberg University

<sup>2</sup>Institute of Atmospheric Physics, Deutsches Zentrum für Luft- und Raumfahrt (DLR e.V.), Oberpfaffenhofen

# Hyperspectral imaging of greenhouse gas hotspots

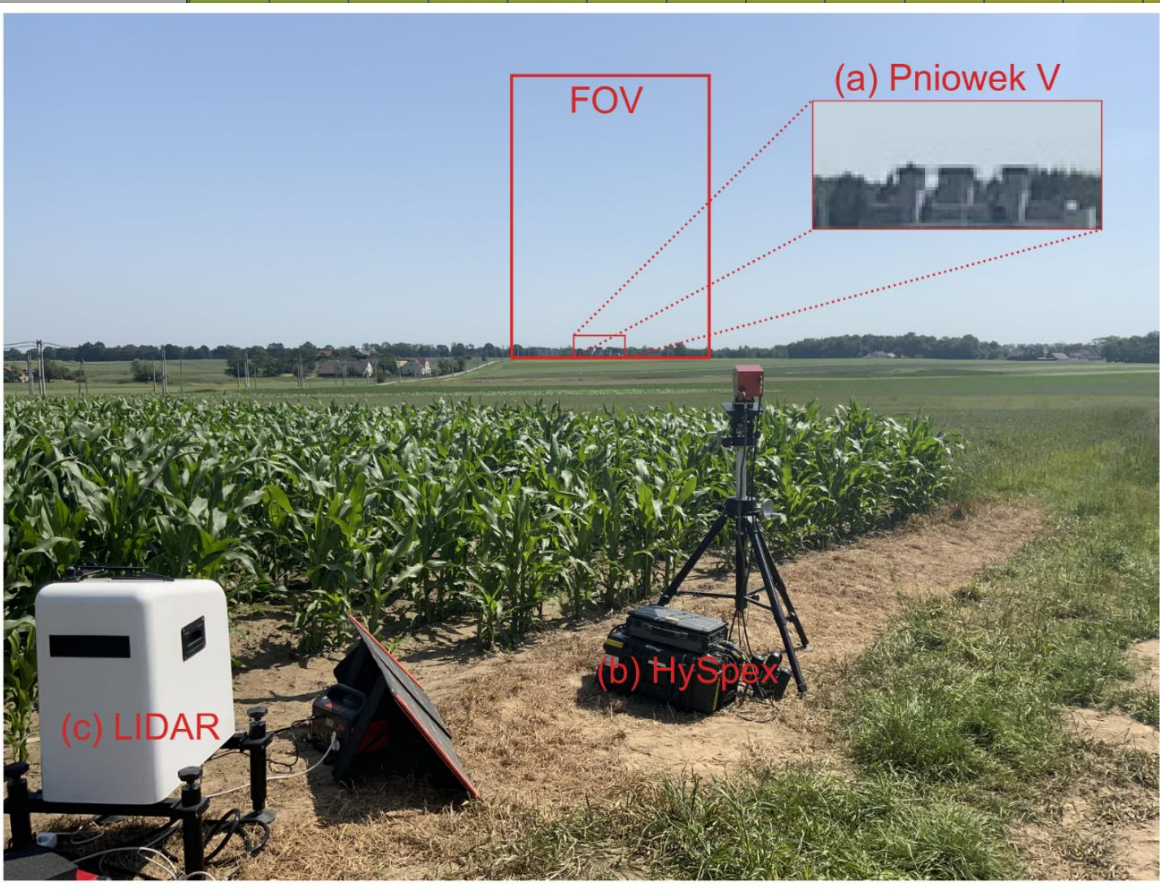
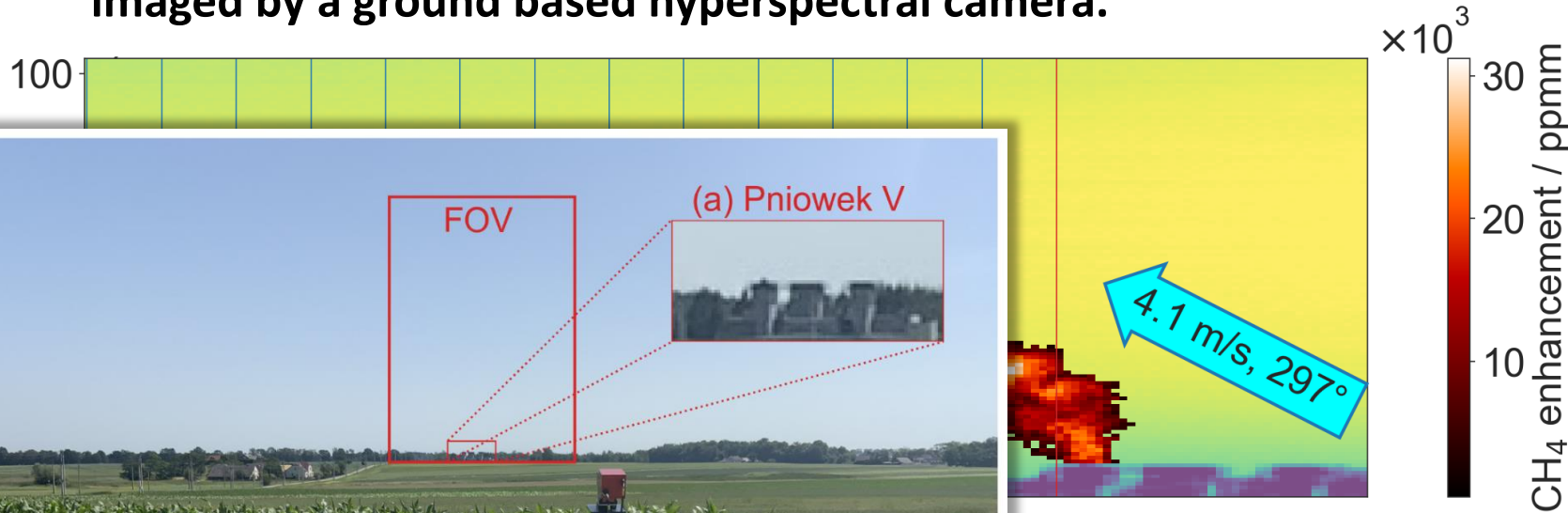
**CH<sub>4</sub> plume from coal mine ventilation in Poland, imaged by a ground based hyperspectral camera.**



- Large localized sources of CO<sub>2</sub> and CH<sub>4</sub> are important contributors to the emission totals (e.g. oil & gas industry, coal mining for CH<sub>4</sub>; power plants, industries, volcanoes for CO<sub>2</sub>).
- Hyperspectral imaging techniques can observe individual plumes of such hotspots.

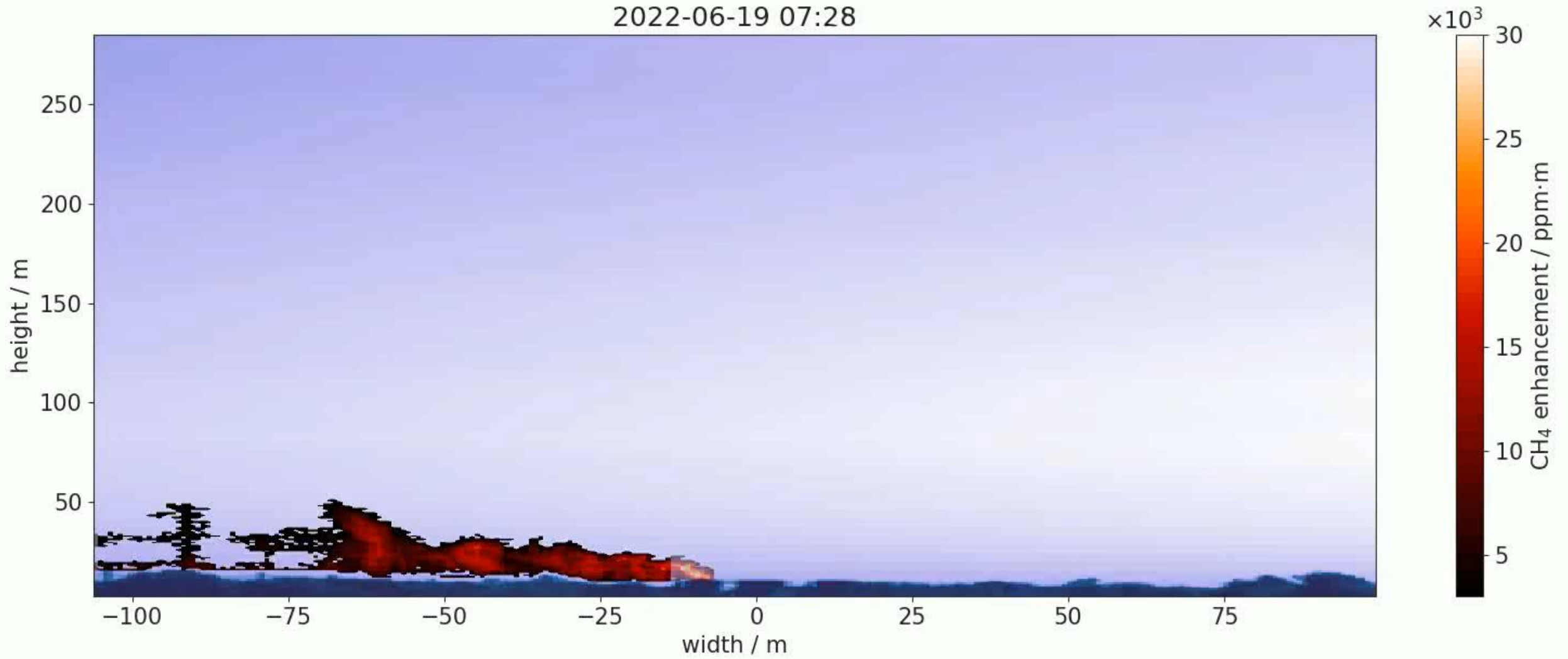
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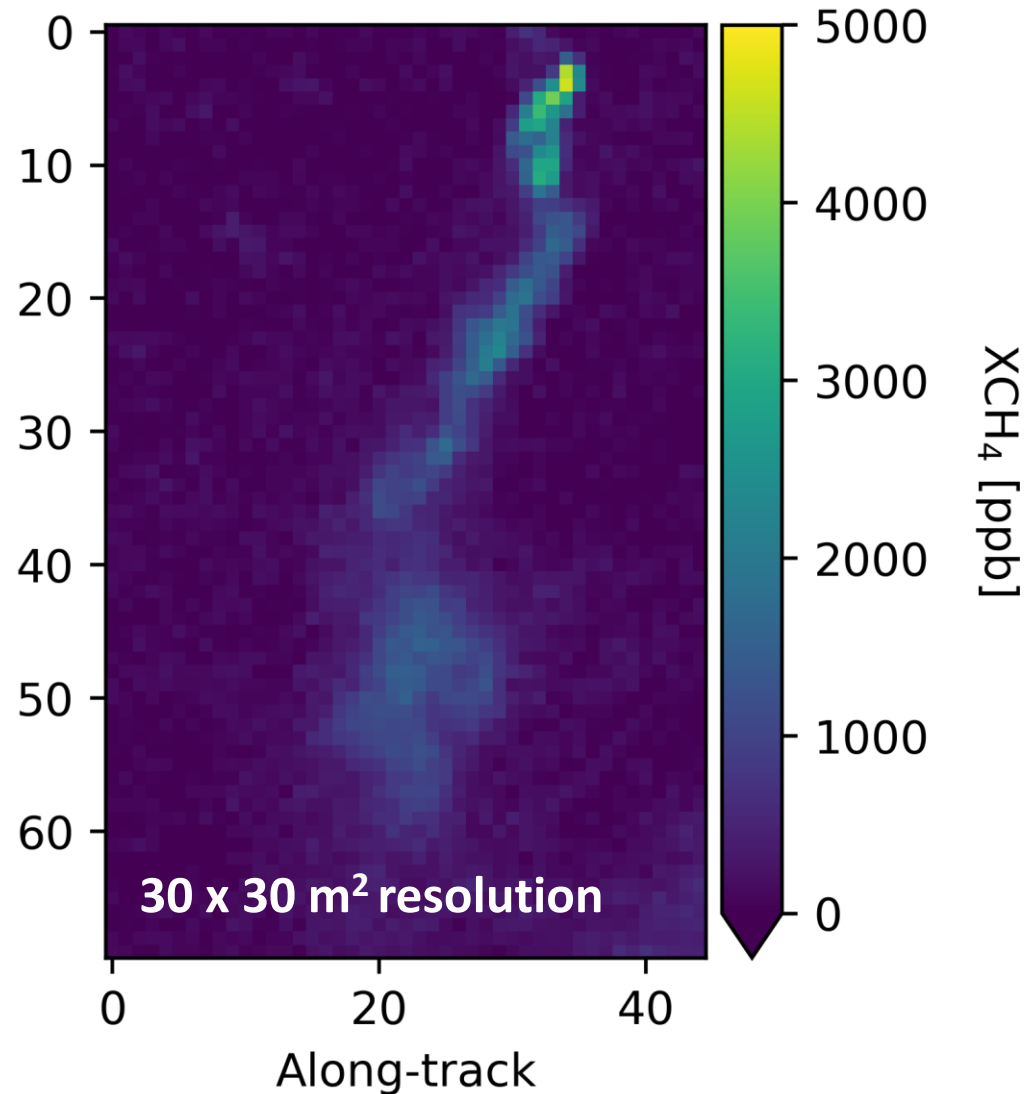
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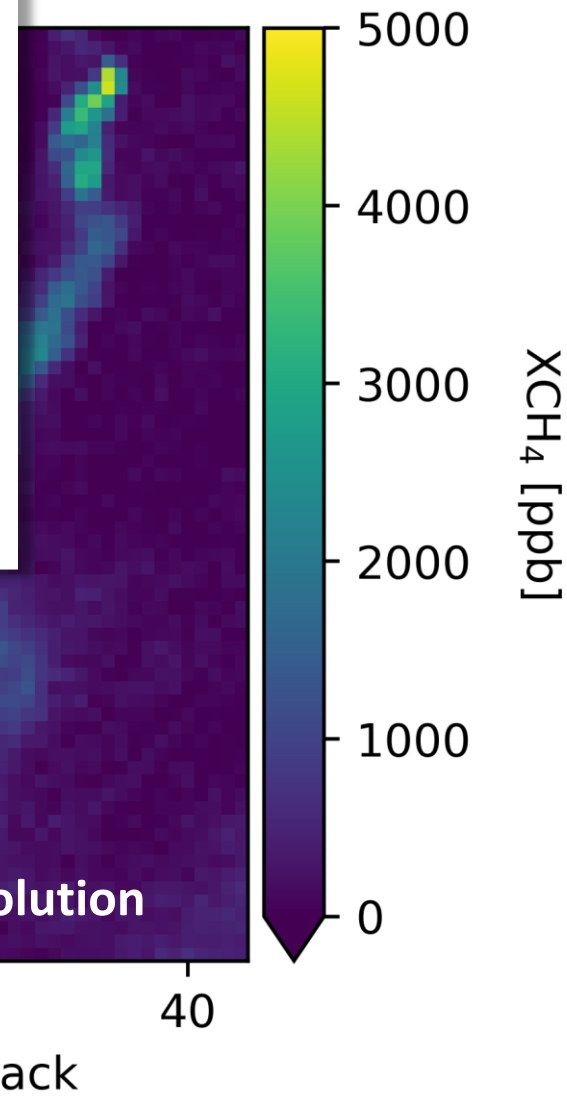
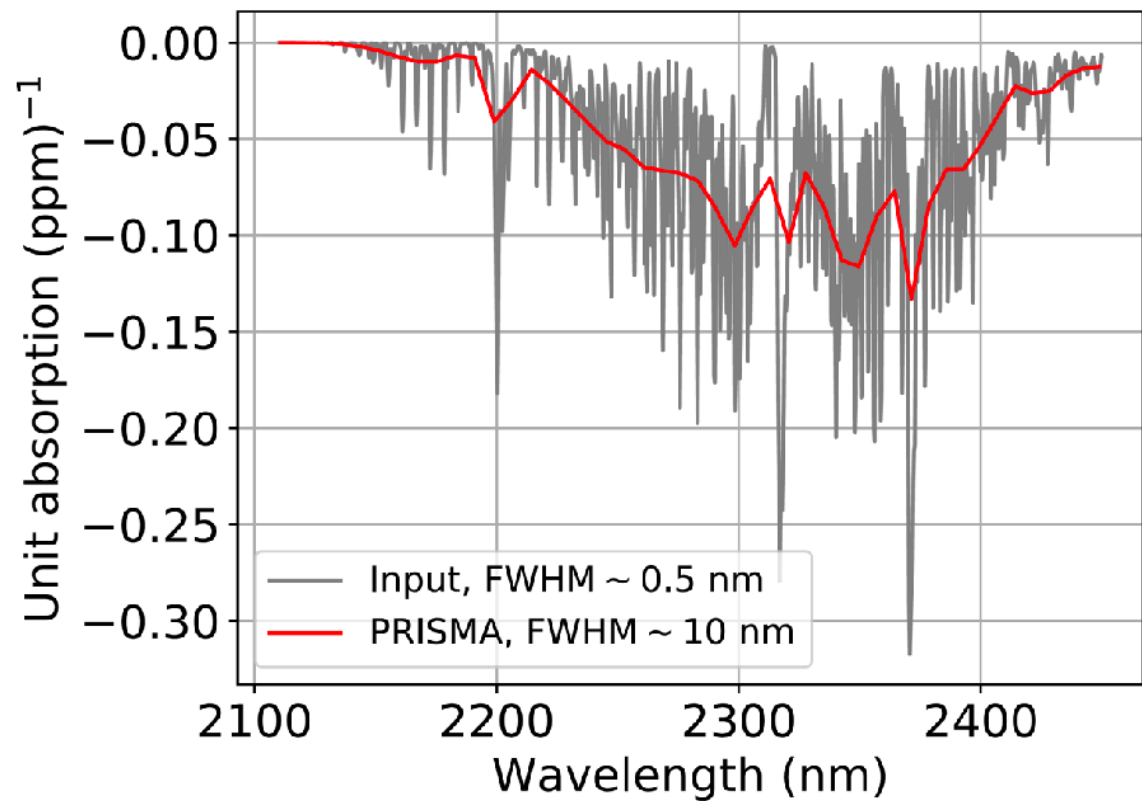
# Hyperspectral imaging of greenhouse gas hotspots

**CH<sub>4</sub> plume from oil & gas production, imaged by the PRISMA satellite**



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# greenhouse gas hotspots



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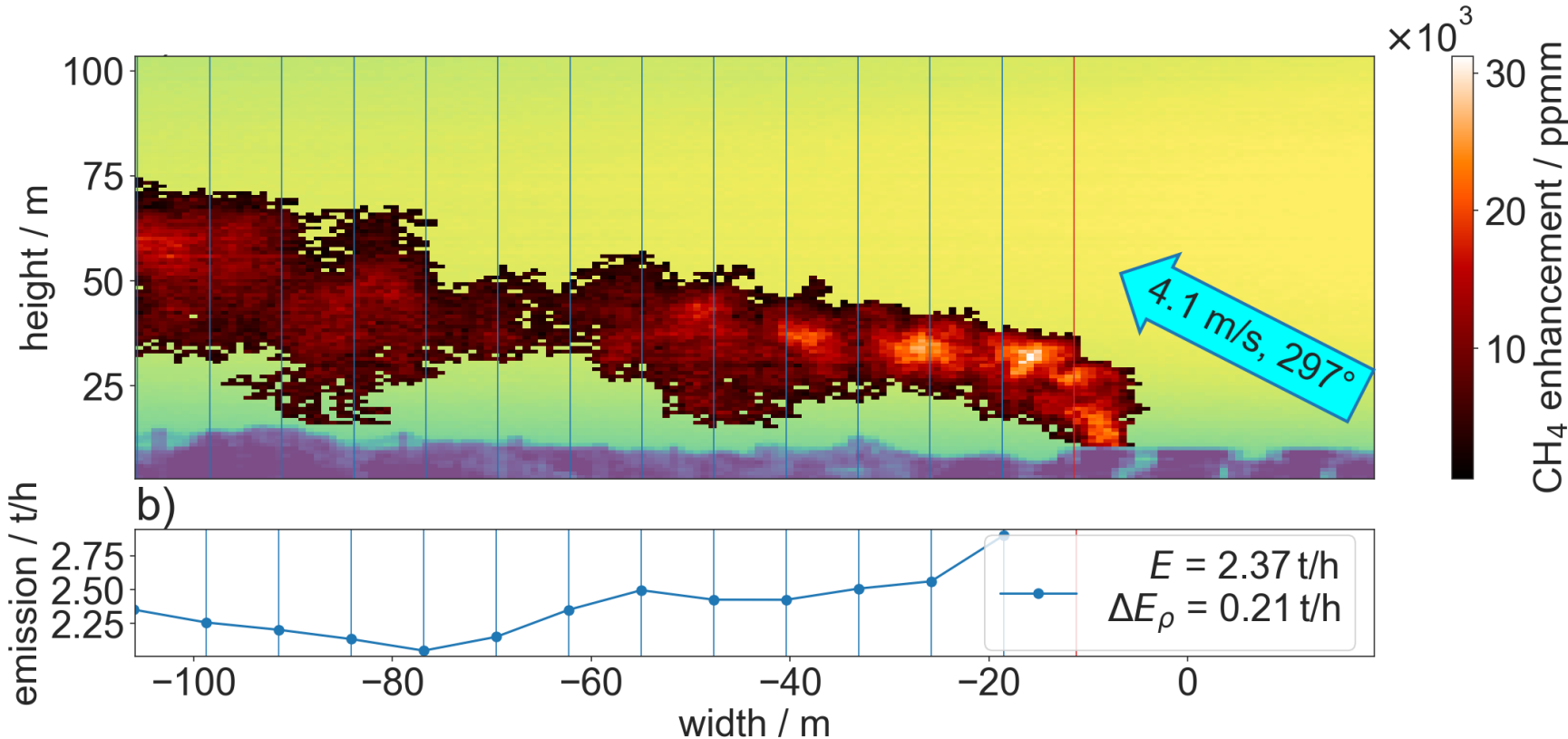
[Guanter, L. et al., RSE, <https://doi.org/10.1016/j.rse.2021.112671>, 2022]

[PRISMA retrievals by Ida Jandl.]

# Context: New missions, new methods, new use cases.

- Julia Marshall's talk on Wednesday, Session 6b, 9:30-10:30h:  
**CO2Image**
- My talk on Wednesday, Session 7a „EnMAP II“, 11:00-12:30h:  
**Fernerkundung von Methanabluffahnen aus EnMAP  
Beobachtungen**
- Here: **CO2KI - Methoden der künstlichen Intelligenz zur skalen-  
und prozessübergreifenden Erfassung von Quellen und Senken  
von Kohlendioxid**

# How to get emission rates from images?

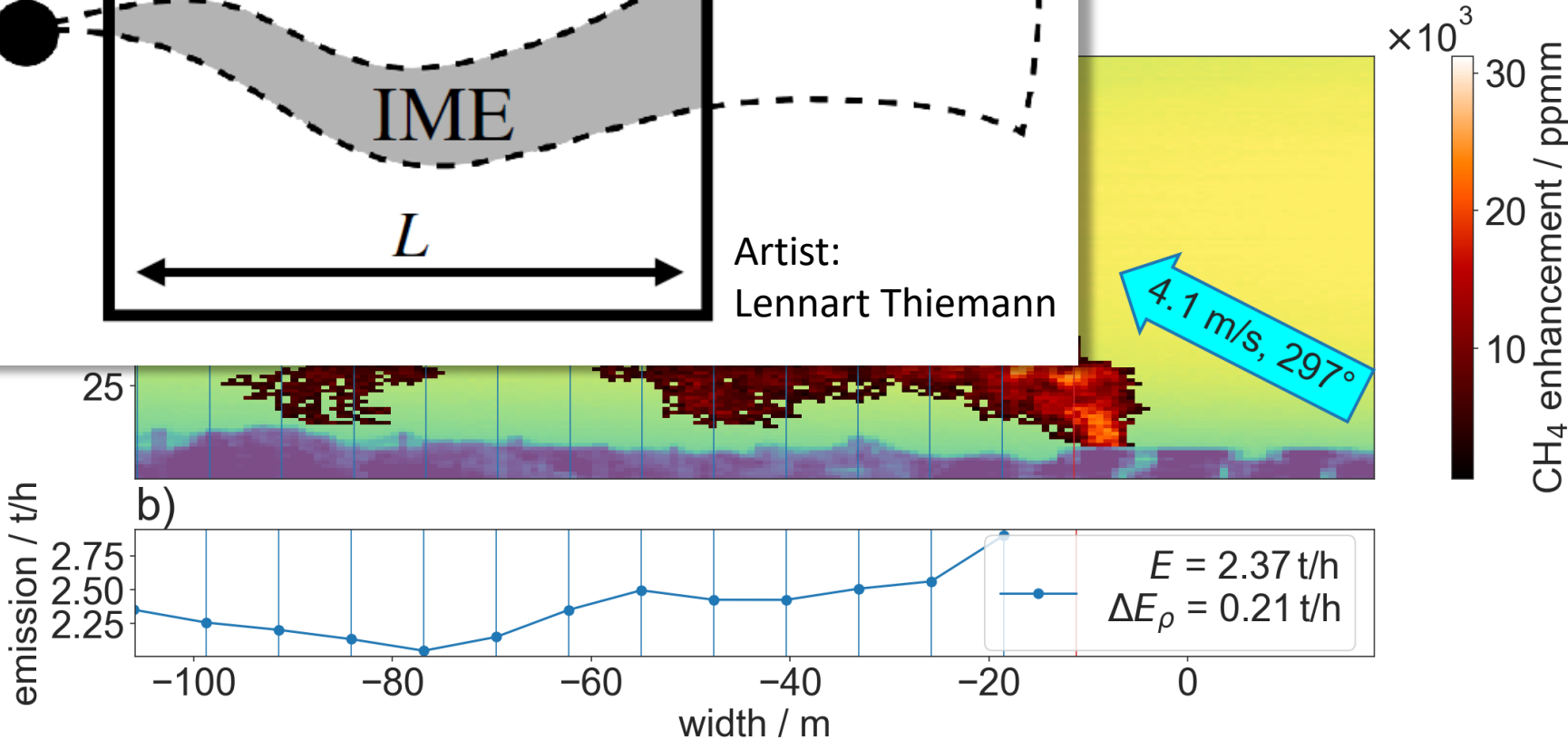
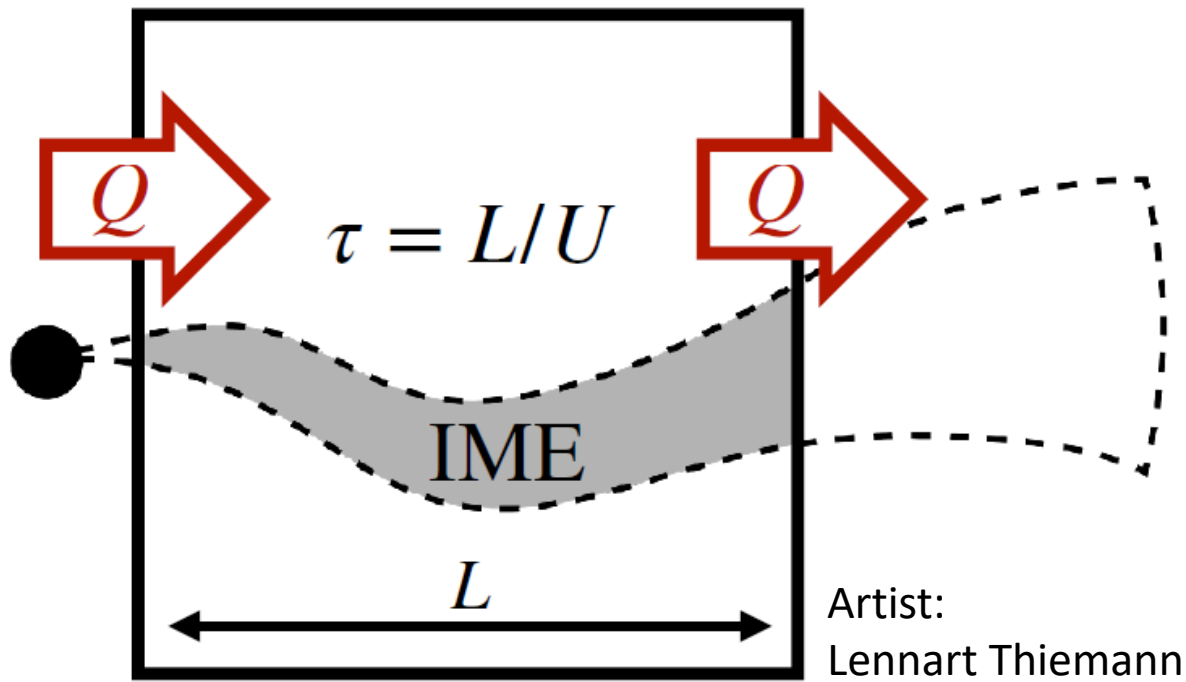


- Turbulent dispersion of the plume out of the source, controlled by various meteorological and surfac parameters.
- Mass balance methods work, but they rely on knowledge of the wind speed and the assumption that an effective wind speed drives a quasi-advective transport:

$$E = M_{\text{CH}_4} / L \times u_{\perp}$$



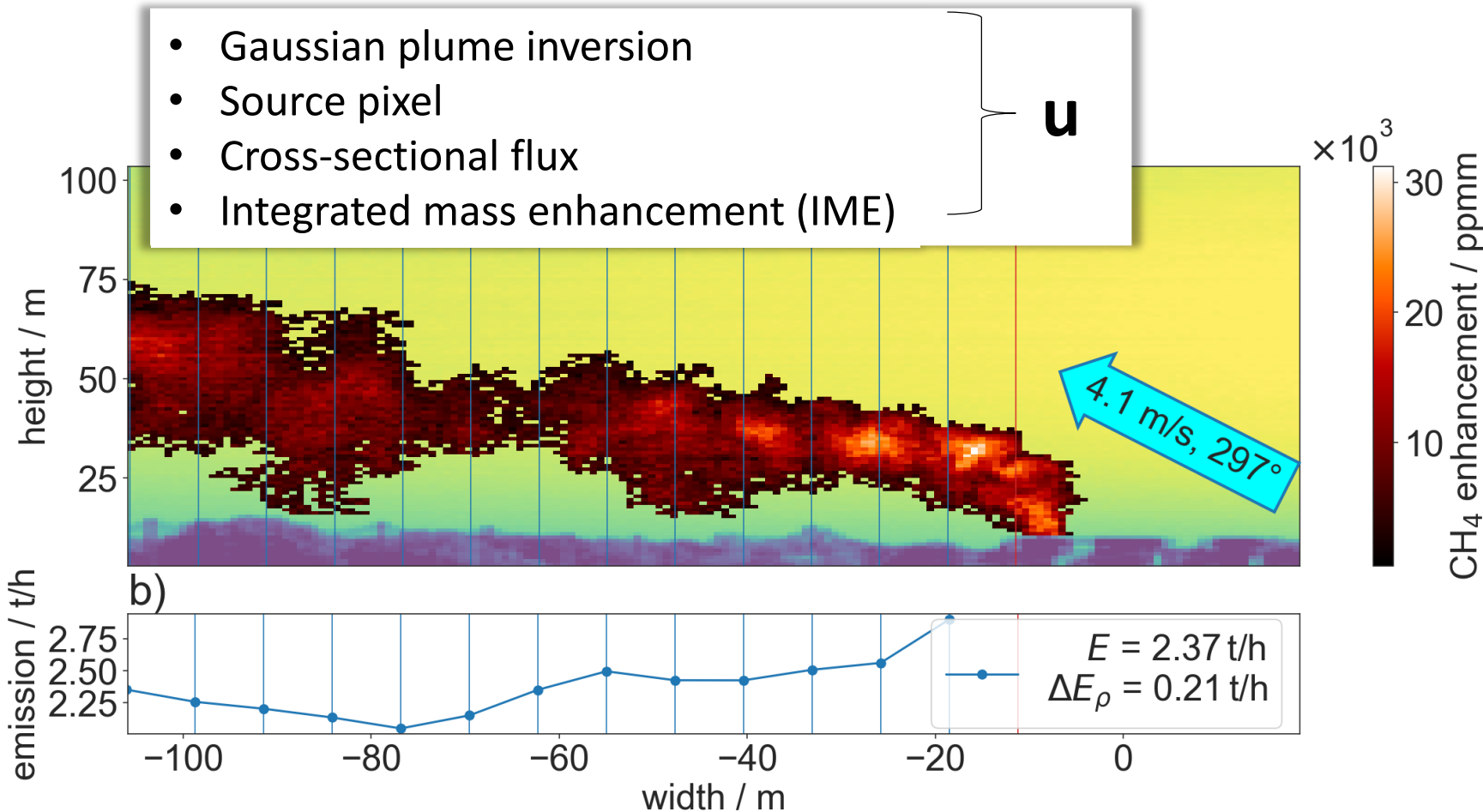
# om images?



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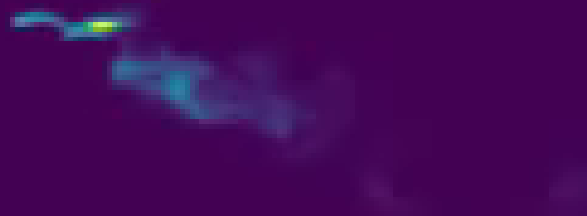
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300 x 300 pixels, 5x5 m<sup>2</sup> resolution



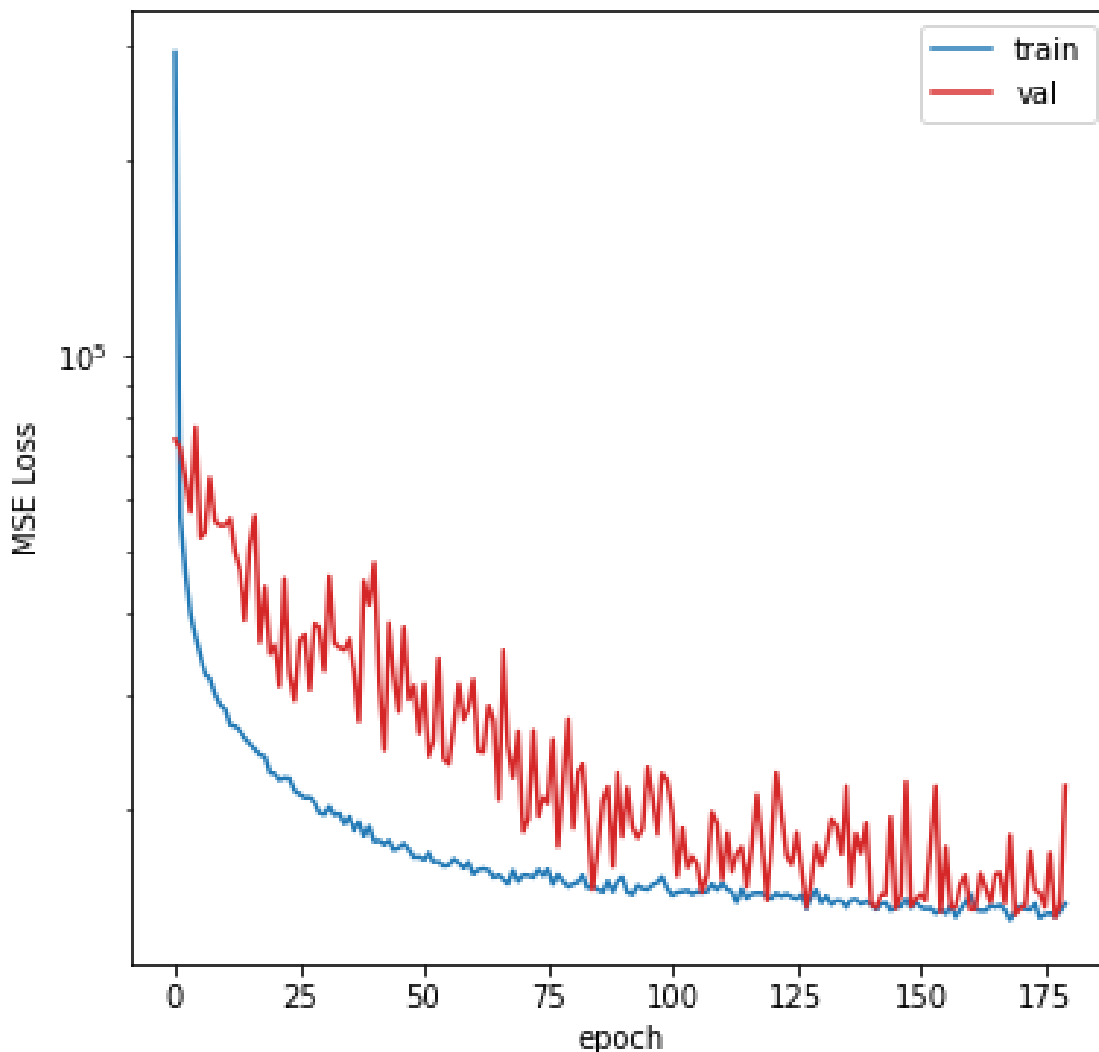
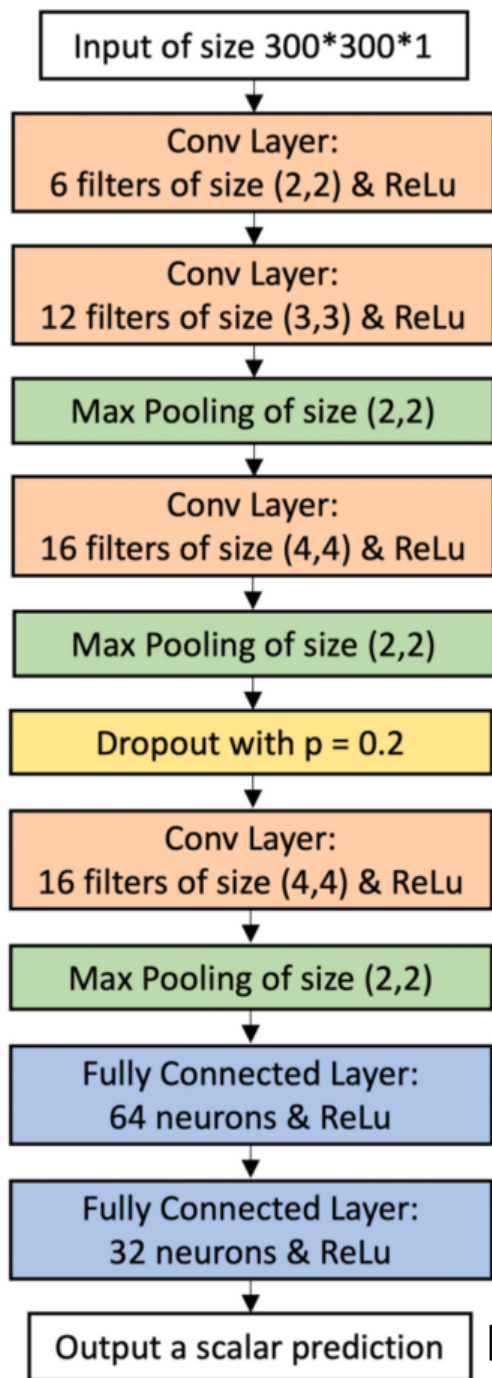
# Try AI.

## Training data: LES simulations at 5 m resolution

- After one hour of spin-up a snapshot was taken every 10 seconds and is used as an independent turbulent realization.
- Overall 7000 plume snapshots with geostrophic wind speeds ranging from 1 to 10 m/s.
- Add Gaussian noise.

[S. Jongaramrungruang et al., “MethaNet ...”, RSE, <https://doi.org/10.1016/j.rse.2021.112809>, 2022]<sup>11</sup>

# Network architecture



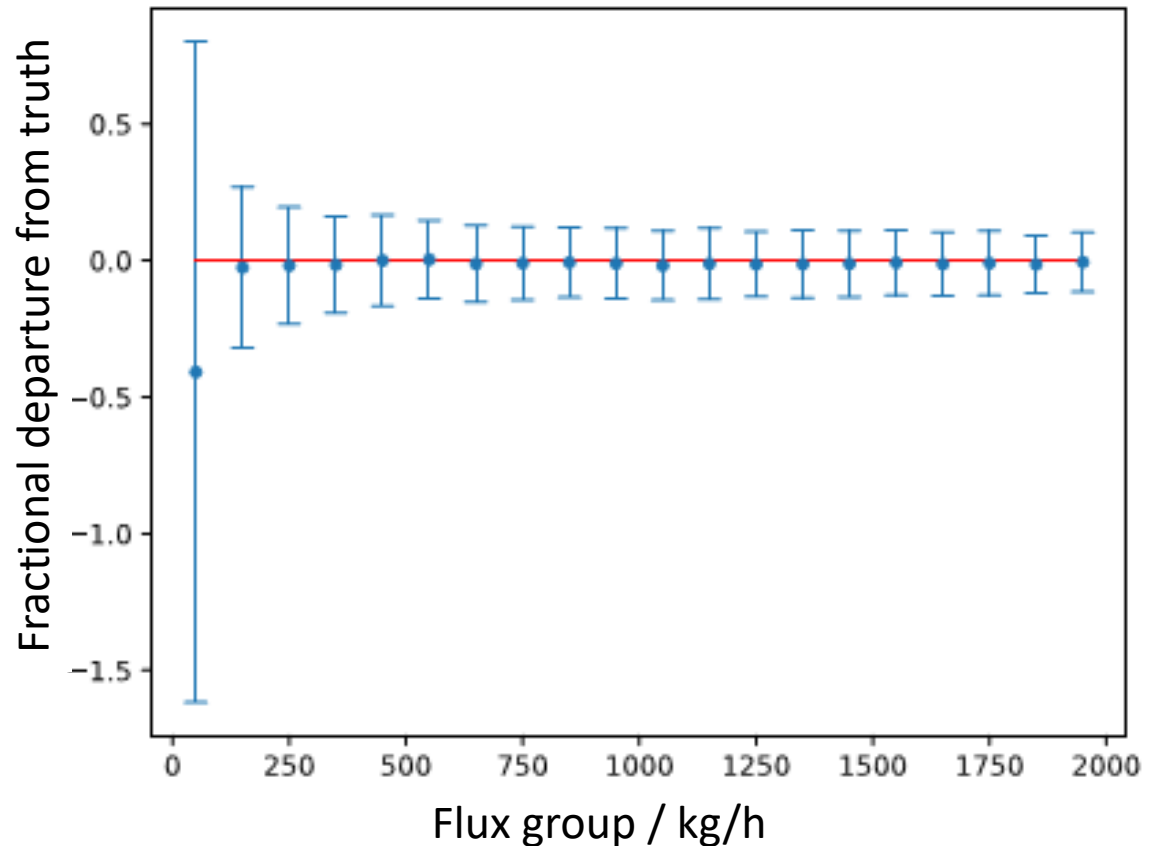
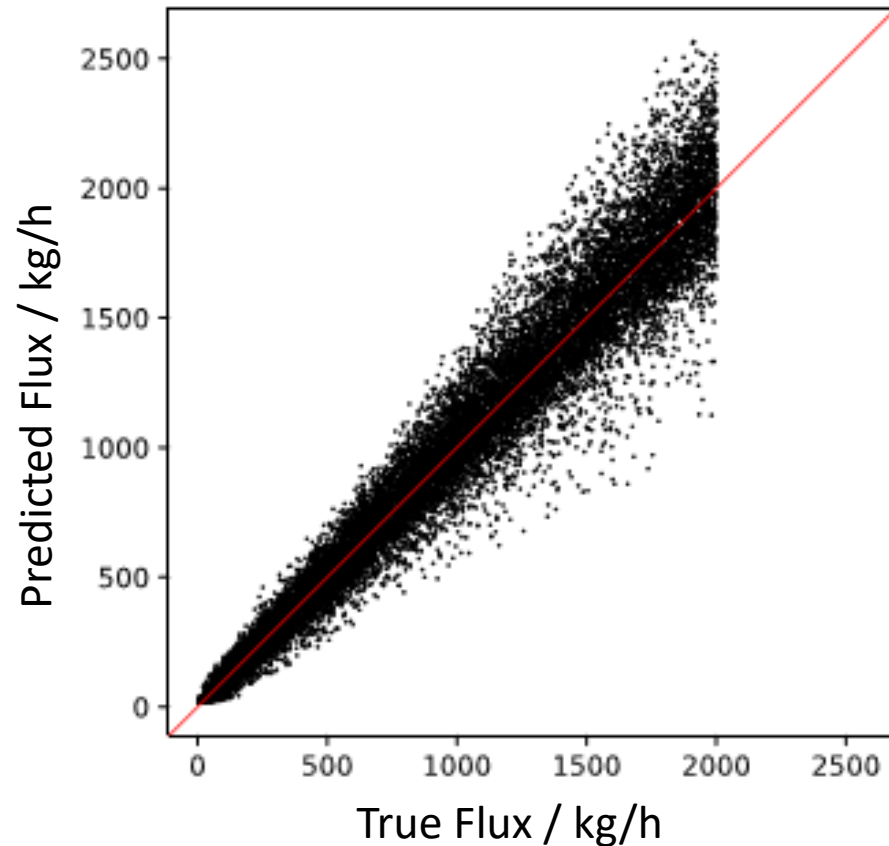
- Starting from the network architecture proposed for MethaNet, we train a convolutional neural network to solve the regression task of flux estimation.
- The optimization criterion is the mean squared error (MSE).
- The available data is split into a training (80%), a validation (15%) and a test dataset (5%).

# Network performance

The average absolute relative deviation across all plumes is 13.8% and 11.9% for plumes over 40 kg/hr.

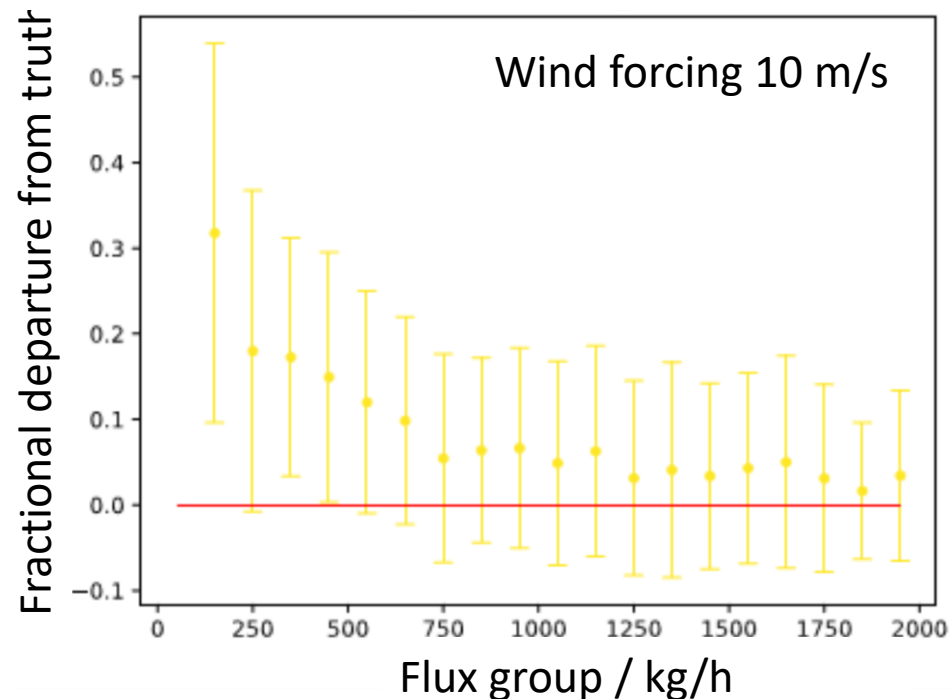
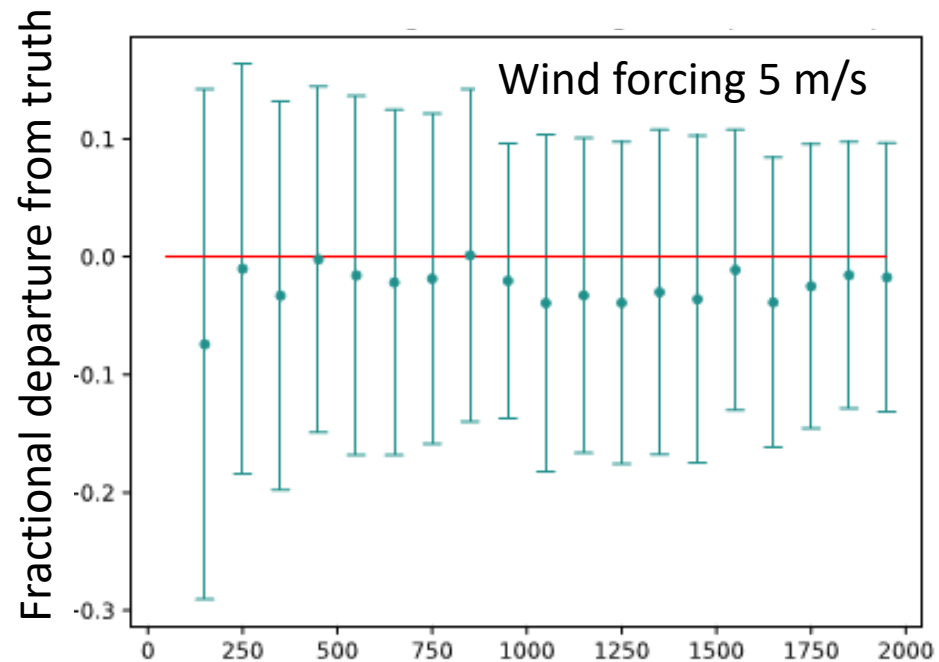
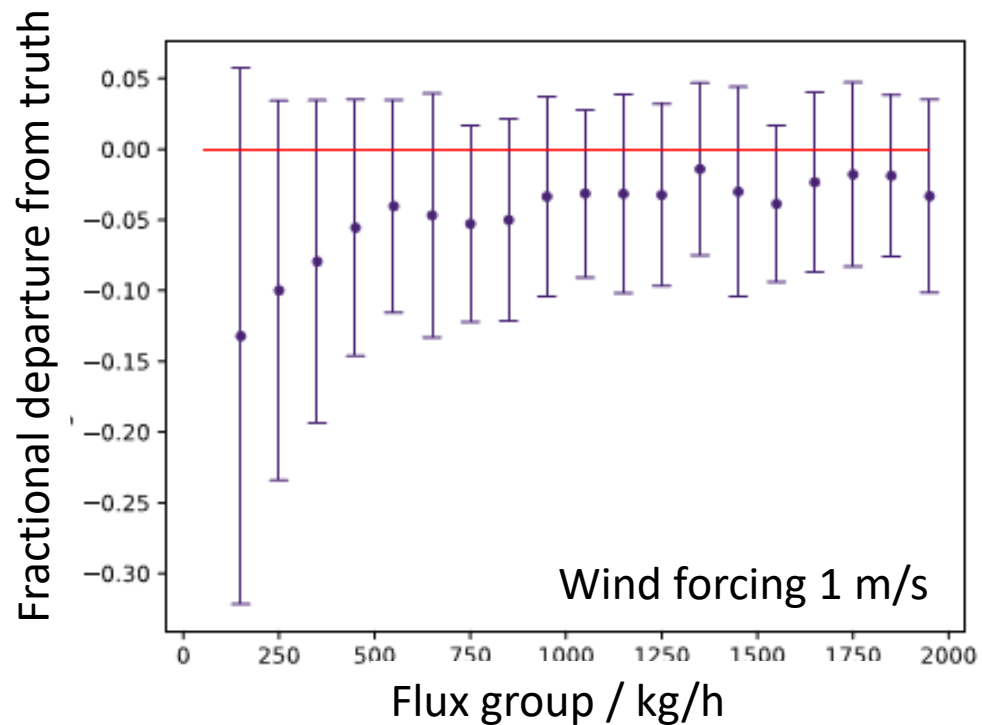
100 kg/h appears the detection limit (for the given noise level).

Systematic biases are very small.



# Network performance

Looking closely, the network appears to produce biases for low/high wind speed for low fluxes: training issue?



# Conclusions / Outlook

- Hyperspectral imaging from satellites, aircraft and ground is a **tool to infer emission rates of large sources**.
- Emission rate quantification **challenged by turbulent dispersion and uncertain knowledge of transport velocity**.
- Synthetic study with **CNNs operating on LES simulations** shows promising results. Next steps:
  - Optimize network design.
  - Make simulations more realistic.
  - Investigate dependence on spatial resolution.
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- My talk on Wednesday, Session 7a „EnMAP II“, 11:00-12:30h: „**Fernerkundung von Methanabluffahren aus EnMAP Beobachtungen**“.

