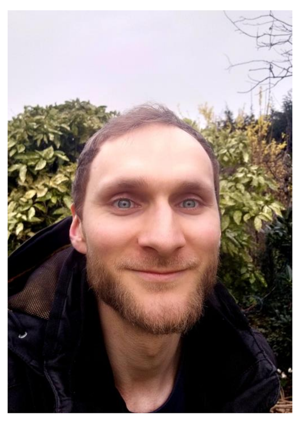
AI-driven flux rate estimation for future satellite missions



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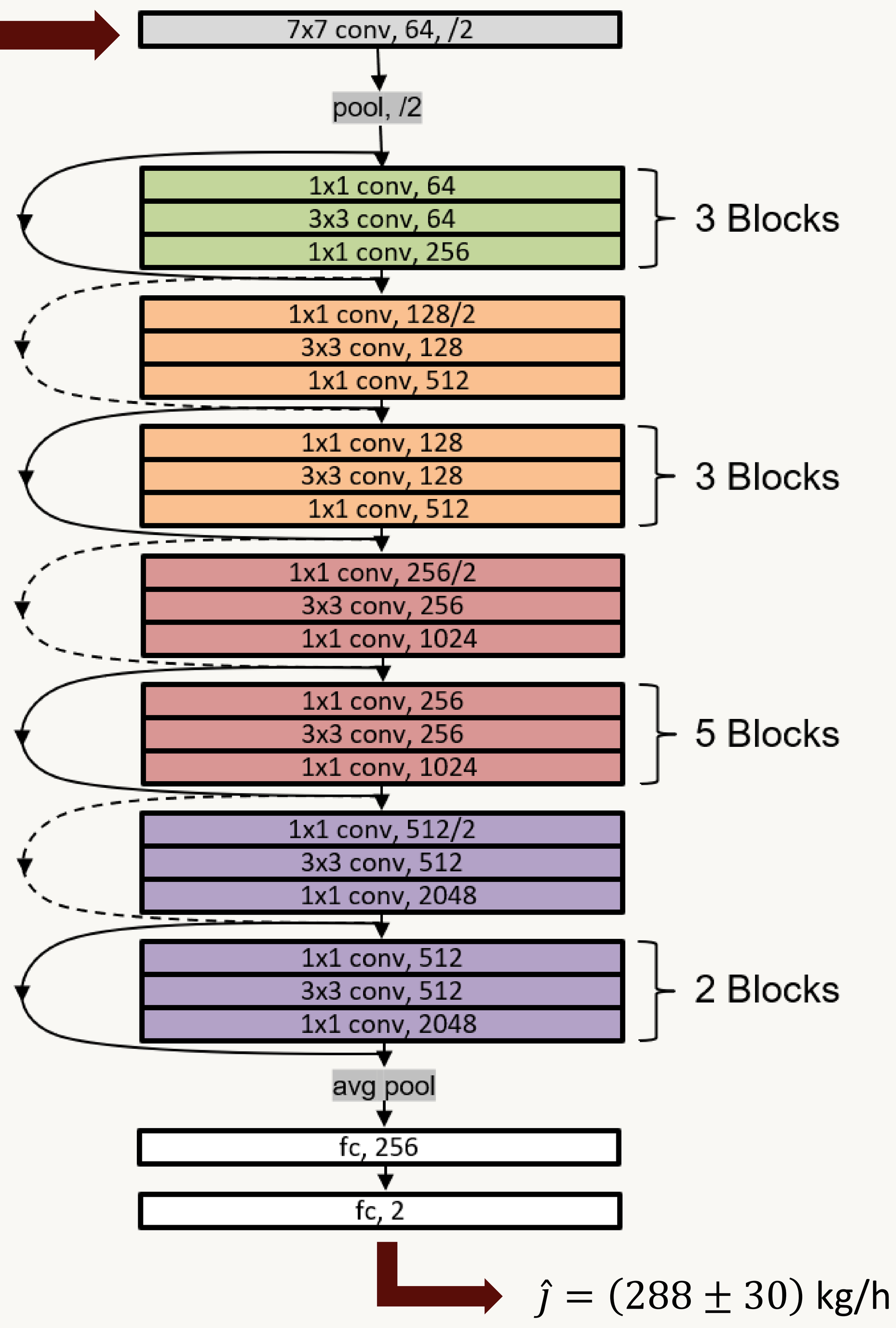
Abstract

- We follow the approach of S. Jongaramrungruang, using information contained in the plume shape[1] to estimate the flux rate without external wind speed information, utilizing deep learning.[2]
- We implemented improvements to the overall methodology to address known issues from previous works and suggest an analysis pipeline that allows the performance of deep learning models to be verified, to make them more robust.
- In addition, we are the first to obtain meaningful error estimates from a deep learning model for the regression task of flux rate estimation.
- The improvements we introduced should be applicable to other studies and lead to an increased performance as well as the ability to obtain uncertainty estimates.

Setup



- We use 7000 images of column-integrated CH_4 LES plumes and 3000 realistic background noise scenes to generate synthetic data with a resolution of 5 m x 5 m.
- The plumes are rotated, shifted and scaled to emulate random wind directions and flux rates and a rotated realistic background noise from AVIRIS-NG flights is added.
- As a last step, a masking threshold of 500 ppm m is applied to remove information unavailable in real measurements and to make the generalization to real world data more stable.
- The data is split into training, validation and test data and fed into a ResNet−50[3] with slight modifications for the regression task.
- The optimization criterion is the Gaussian negative log likelihood loss:

$$\ell(x,\theta) = \frac{1}{2}\left(\log(\sigma^2(x,\theta)) + \frac{(\hat{j}(x,\theta) - j)^2}{\sigma^2(x,\theta)}\right) + const$$

Results

threshold $kg\,h^{-1}$	MPE %	MAPE %	R %
0	3.24	13.86	97.98
40	−0.47	10.29	97.98
100	−0.72	9.48	97.98

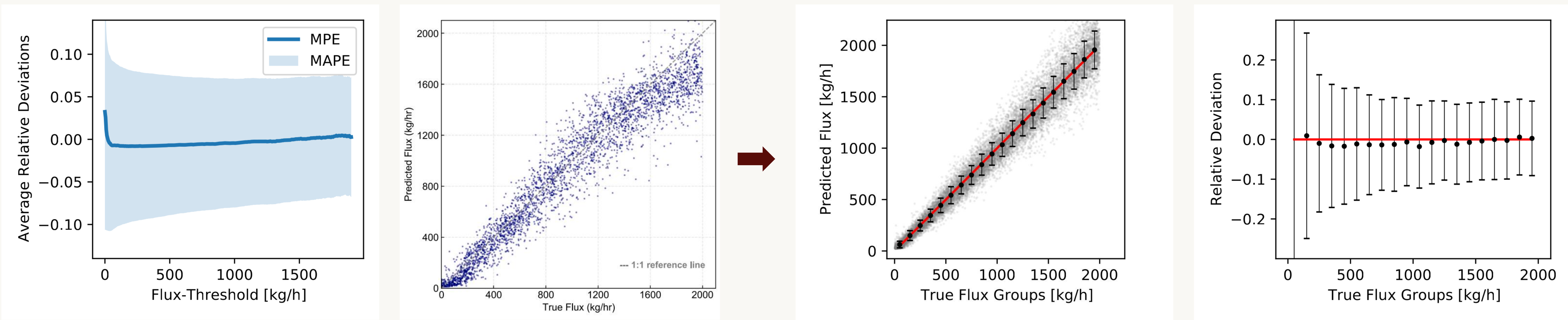
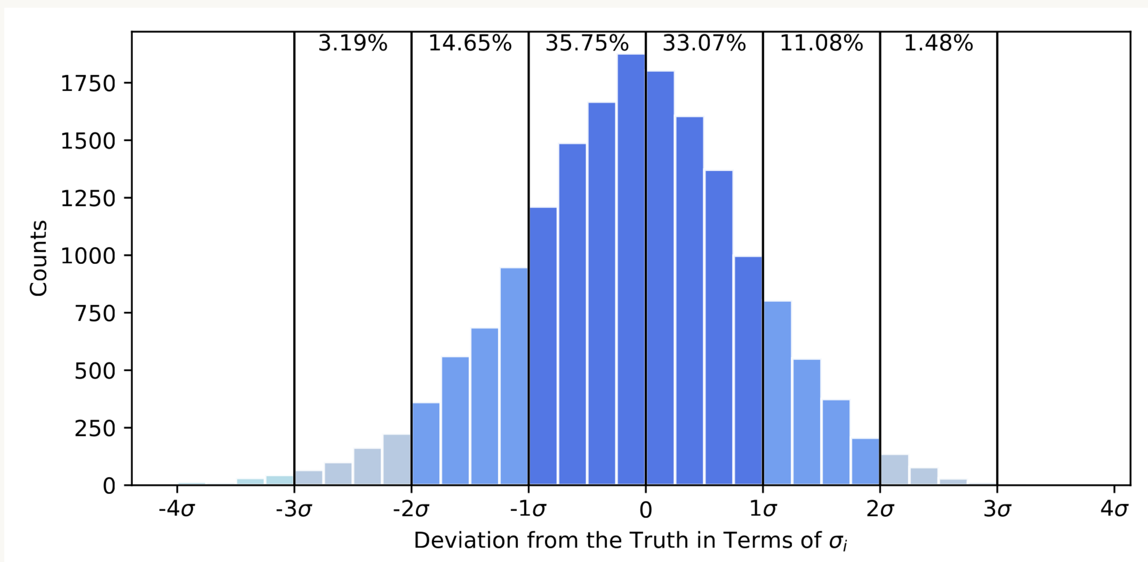


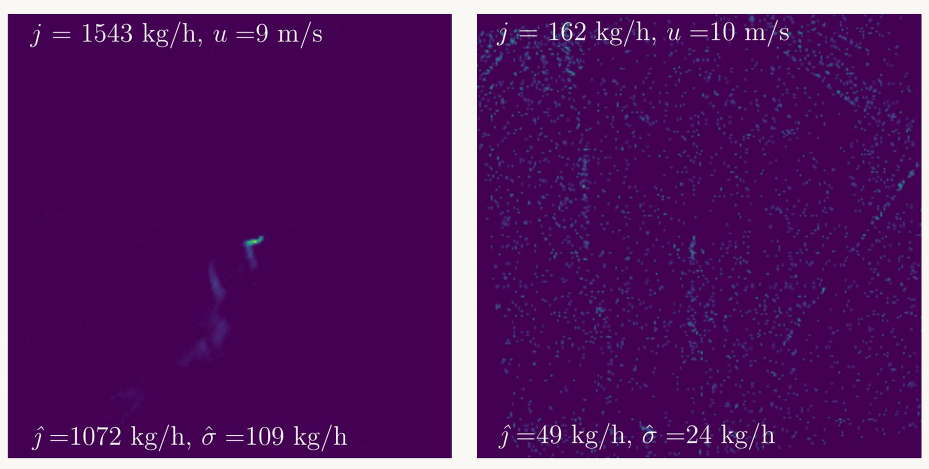
Figure taken from [2]



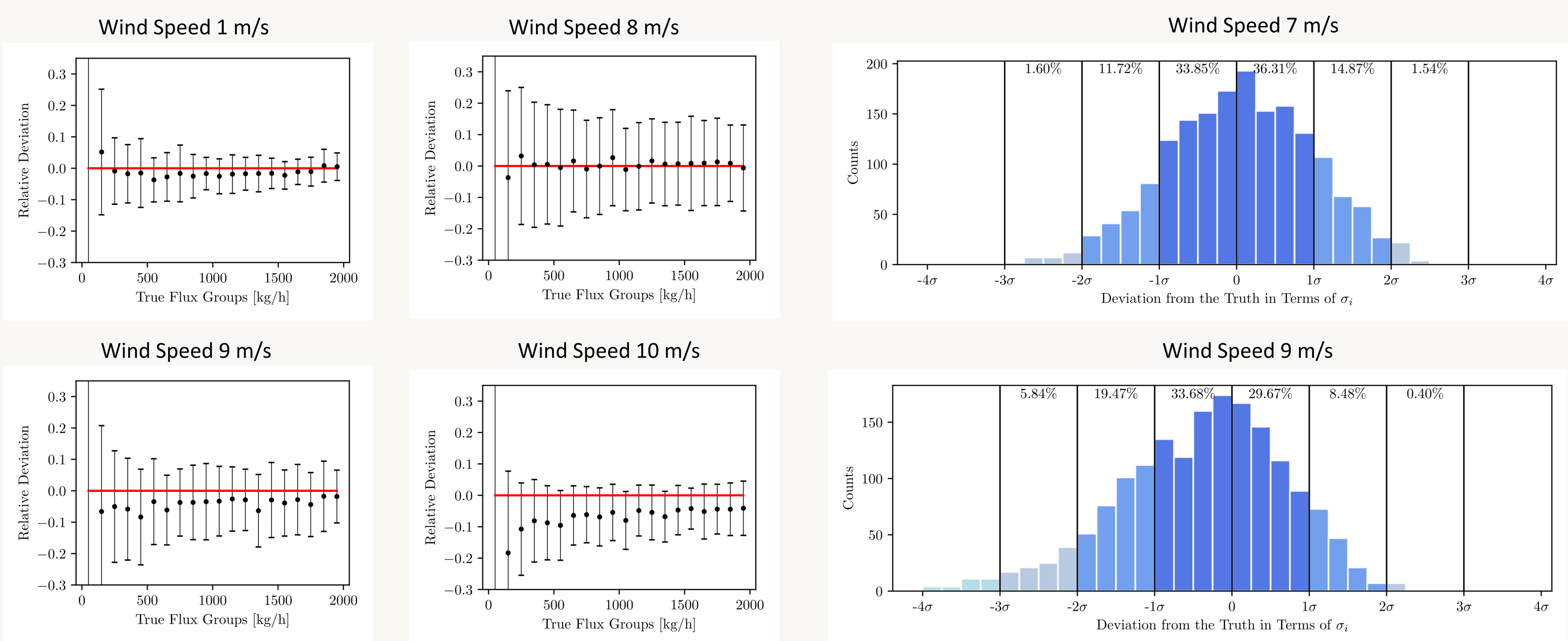
- The model shows very few signs of bias over the whole flux domain, with the exception of plumes in the range from 0 kg/h to 100 kg/h.
- We use the mean percentage error (MPE), the mean absolute percentage error (MAPE) and the Pearson correlation coefficient (R) as summary statistics for the model performance.
- The predictions of the model seem to stabilize around 40 kg/h and, due to the low biases, the performance remains stable for arbitrary flux distributions.
- The differences between the true and the predicted flux rates with respect to their respective error estimates follow a normal distribution over the whole test dataset.

Analysis

- Looking at individual wind speed ensembles reveals a systematic bias for 9 m/s and 10 m/s.
- In addition, a wind-speed-dependent instability is observable for low flux rates.
- The bias shows an impact on the error estimates for geostrophic wind speeds of 9 m/s or 10 m/s.



Examples of scenes with poor model performance



References

[1] S. Jongaramrungruang et al. “Towards accurate methane point-source quantification from high-resolution 2-D plume imagery”. In: Atmospheric Measurement Techniques 12.12 (2019), pp. 6667–6681. doi: 10.5194/amt-12-6667-2019.
[2] S. Jongaramrungruang et al. “MethaNet – An AI-driven approach to quantifying methane point-source emission from high-resolution 2-D plume imagery”. In: Remote Sensing of Environment 269 (2022), p. 112809. issn: 0034-4257. doi: https://doi.org/10.1016/j.rse.2021.112809.
[3] He, Kaiming et al. “Deep Residual Learning for Image Recognition.” 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2015): 770−778.

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