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Poster
To support the goals of the Paris Agreement, monitoring and verification support (MVS) capacities focussing on anthropogenic greenhouse gas emissions are being developed, such as the EU’s emerging Copernicus CO2 Service and Germany’s ITMS (Integriertes Treibhausgas-Monitoringsystem). Satellite concepts capable of measuring atmospheric CO2 and CH4 concentrations on small spatial scales (10s of meters) have emerged as potential contributors to such MVS systems, through their ability to image the exhaust plumes of individual facilities. To quantify emissions based on these plume images, traditional mass balance methods require an accurate knowledge of the effective speed of the wind that transports the detected CO2 or CH4 plume. Uncertainty in the wind speed is the largest source of uncertainty in the estimated emissions. It has been proposed, however, that machine learning approaches might be able to estimate emission rates directly from the turbulent plume images without the need to impose wind speeds from external sources.

Here, we present our progress on developing a deep-learning-based emission rate estimator for plume images using convolutional neural networks. Our main focus lies on the improvement of the quality and certainty of deep learning models. Therefore, we provide a model that is capable of providing estimates with, on average, little to no bias over a large scale of flux rates. We present a feasible solution to existing biases, leading to a Pearson correlation coefficient of 98%. In addition, our model provides error estimates alongside its flux predictions, making a first step to improve the certainty of estimated predictions. Further, we want to highlight limitations to this approach that we encountered during the performance analysis and suggest possible future improvements. Thus, we hope to make deep-learning-based methods a more stable and powerful approach that is capable of efficiently analyzing large amounts of incoming data.
Poster PDF
plewa-thomas-poster.pdf
Meeting homepage
IWGGMS-20 Workshop