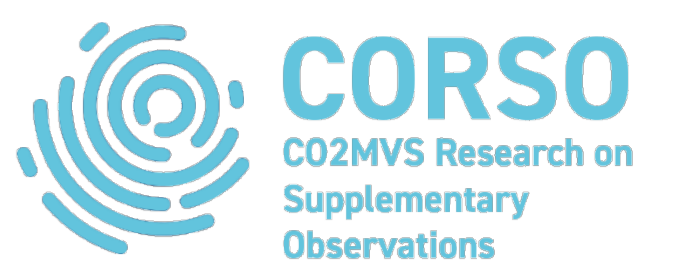


# Bayesian denoising of noisy trace gas satellite images using co-registered trace gas images for improved hot-spot emission estimation



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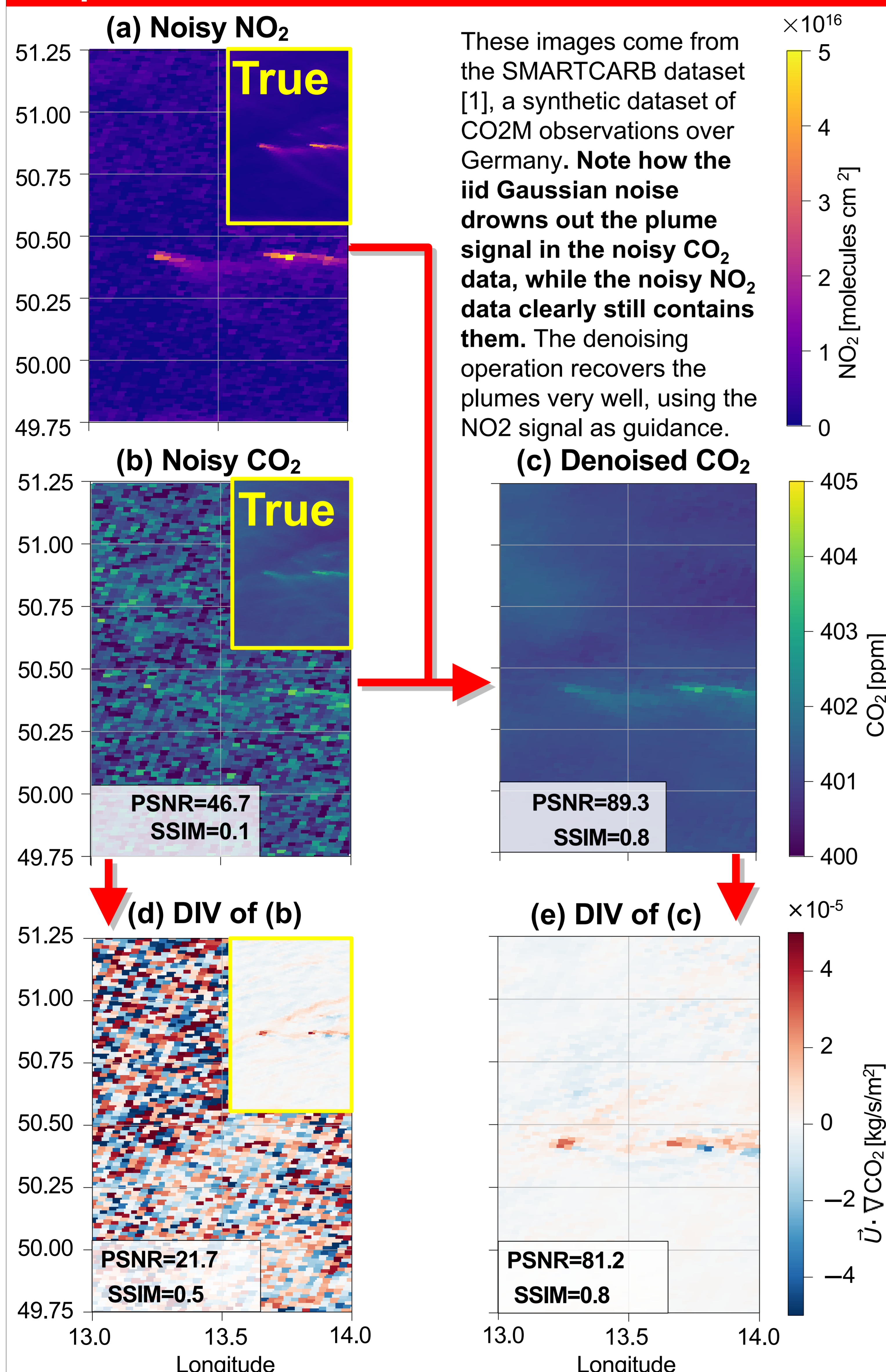
## Introduction

Satellites typically record total columns for various atmospheric trace gases, with varying signal-to-noise ratios (SNR). For example:

- TROPOMI:
  - NO<sub>2</sub> is measured with excellent SNR
  - SO<sub>2</sub> is measured with lower SNR
- CO2M:
  - NO<sub>2</sub> is measured with excellent SNR
  - CO<sub>2</sub> is measured with lower SNR

The question: **can we use the signal with excellent SNR to improve the signal with lower SNR?** The high SNR signal contains *similar* information regarding hot spot plumes.

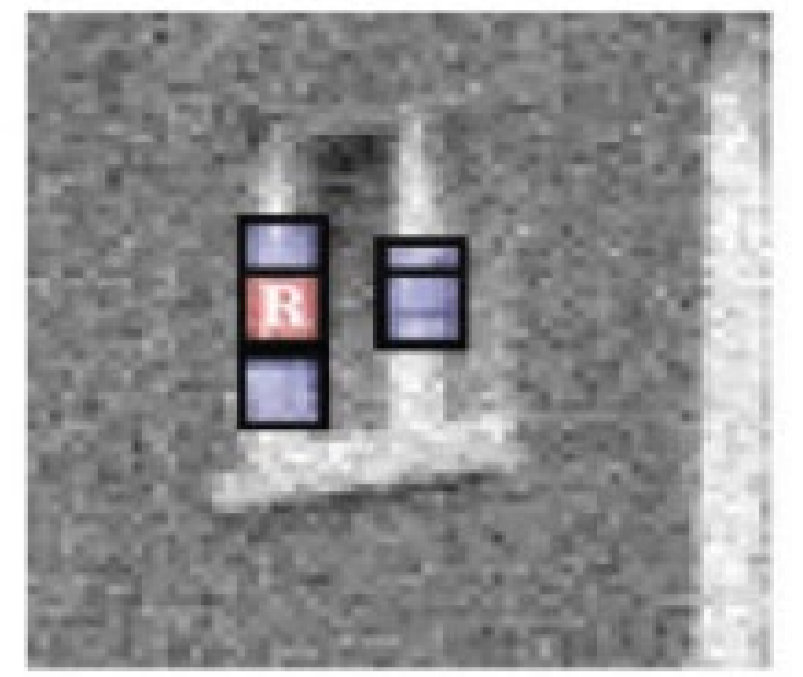
## Proposed method



The advantage of the proposed method is that we **require less data to obtain reliable emission estimates**. We can for example improve the SNR of divergence maps by improving the SNR of individual overpass images. Then we should get higher accuracy in emission estimates, and possibly a higher temporal resolution.

## Method description

We combine two methods. **The first** is a technique called block matching and 3D filtering (**BM3D**, [2]) from computer vision. It is a minimum mean square estimator (**MMSE**) that uses self-similarity of image *patches*. By using it for a multichannel image with normalized data, it uses the self-similarity in the high SNR image patches for denoising, and the same selected patches are then used to denoise the corresponding low SNR image. In other words, the high SNR data guides the denoising.

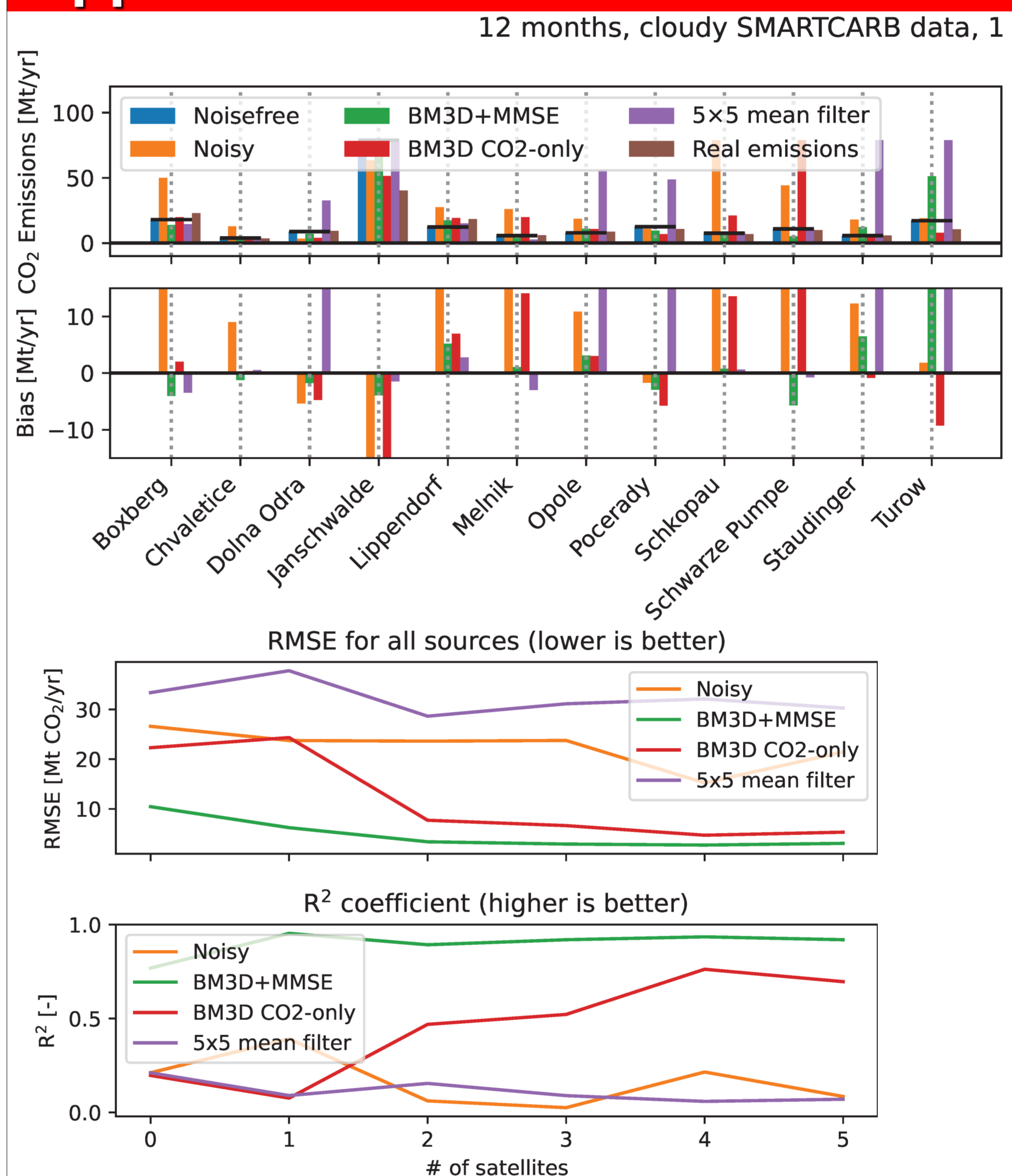


**The second** method is another **MMSE**, that uses the joint presence of signal enhancements in the satellite image. This Bayesian optimal estimator of the noise free CO<sub>2</sub> field can be obtained fully from the data as

$$\hat{c} = [1 \ 0] (I - C_{nn} C_{dd}^{-1}) (\vec{M} - E[\vec{M}]) + E[c]$$

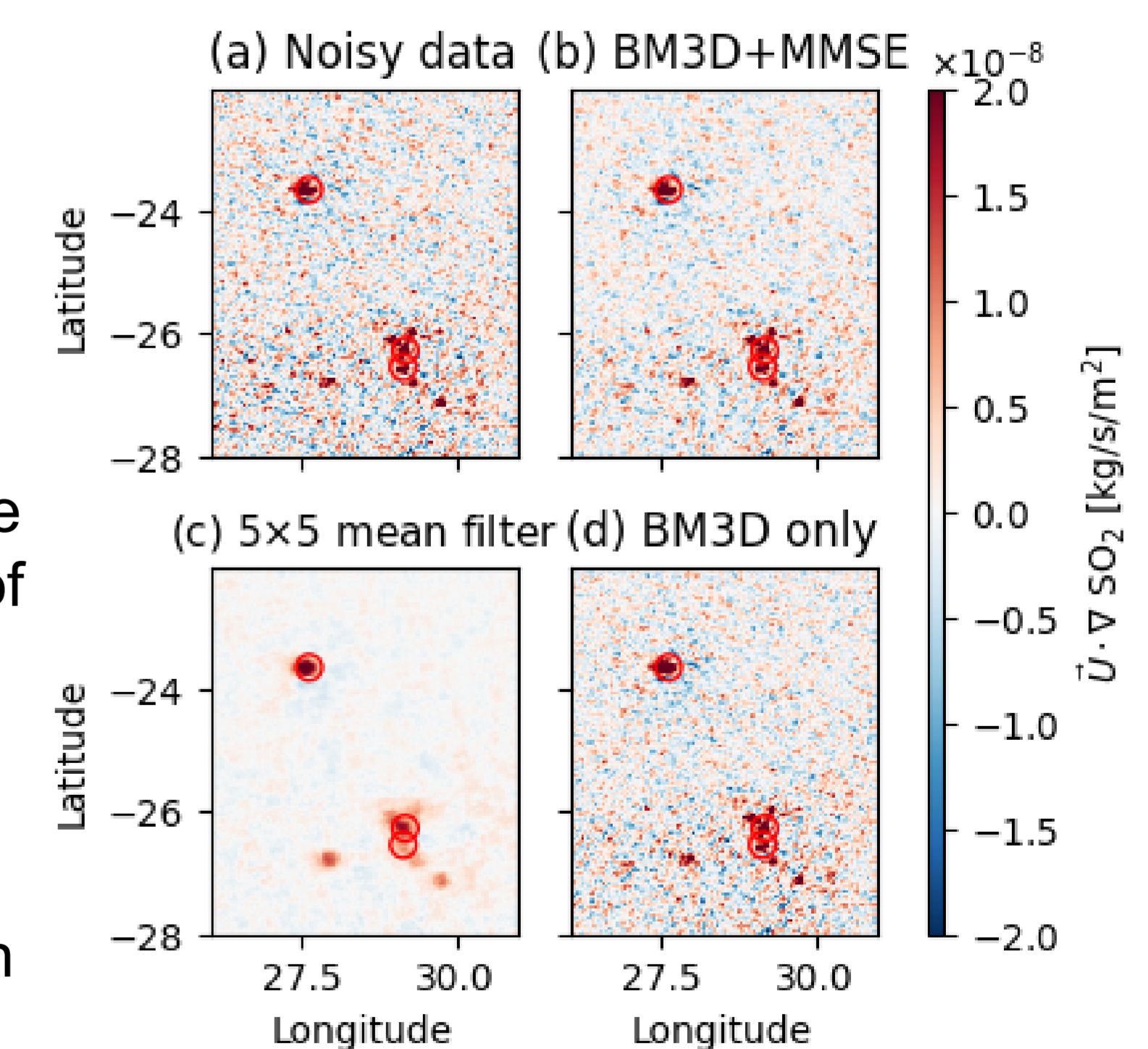
Here,  $C_{nn}$  is the noise covariance matrix,  $C_{dd}^{-1}$  is the (inverse of) the data covariance matrix, and  $E[\vec{M}]$  is the expected value for the multichannel data  $\vec{M}$  (e.g., a vector of CO<sub>2</sub> and NO<sub>2</sub> data), and  $E[c]$  is the expected value for the single channel low SNR data  $c$  (e.g., CO<sub>2</sub>).

## Application to SMARTCARB data



## Application to TROPOMI data

We applied the denoising techniques on a full year (2021) of TROPOMI NO<sub>2</sub> and SO<sub>2</sub> data, to denoise the SO<sub>2</sub> data, and the corresponding divergence maps. In the example given on the right, we obtain divergence maps with 42% less noise when using the proposed approach of BM3D+joint MMSE denoising. Using BM3D only, yields only an 18% improvement. However, in our tests, emission estimates of three sources in the South Africa region is not much affected by the denoising.



## Conclusions & outlook

- We have outlined a quick (<1 second) method which can be used to **denoise low SNR images using co-registered high SNR images**
- We have tested the method for the divergence method, and have shown that it can improve the results for the synthetic SMARTCARB dataset, but see no big differences when using TROPOMI data.