# Supplementary Materials: Pixel size and revisit rate requirements for monitoring power plant $CO_2$ emissions from space

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## 1. Pixel size simulated biases and additional results

Section 2.4 of the main text briefly discussed the biases used in the simulations. In section 1.1 we describe how each bias is generated, and in section 1.2 we show the simulation results for each bias individually.

### *1.1. Generating the biases*

Biases are generated in arbitrary units, and are usually normalized to have maximum values $\pm 1$. This allows for easy scaling of the bias to a desired maximum $XCO_2$ anomaly at run time.

#### 1.1.1. Topography bias

Kiel *et al.* [1] showed how small miss-specifications in the geolocation of OCO-2's footprints led to erroneous $X_{CO_2}$ observations related to steep topography. We simulate this bias by generating topography in the FoV and then computing the gradient of the topography.

Topography is generated with Perlin noise using the `noise` package for python (https://github.com/caseman/noise). The topography is normalized to lie between 0 and 1. Figure S1 shows the topography generated.

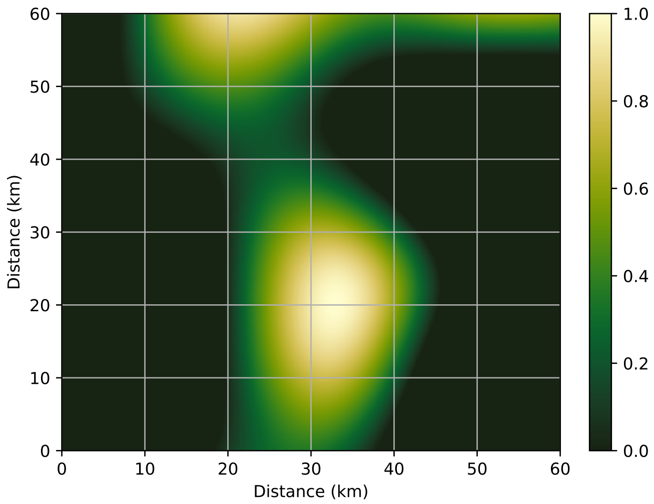


**Figure S1.** Simulated topography (arbitrary units, normalized by the maximum height so the values are between 0 and 1.)

First, we compute the 2-dimensional gradient of the topography. Then, to get a scalar bias from the vector gradient, we compute the directional derivative in the direction $\mathbf{v} = (1/\sqrt{5}, 2/\sqrt{5})$, and again normalize the values between 0 and 1. We also compute the norm of the gradient. Figure S2 shows the $x$ and $y$ components of the gradient, the norm of the gradient, and the directional derivative.

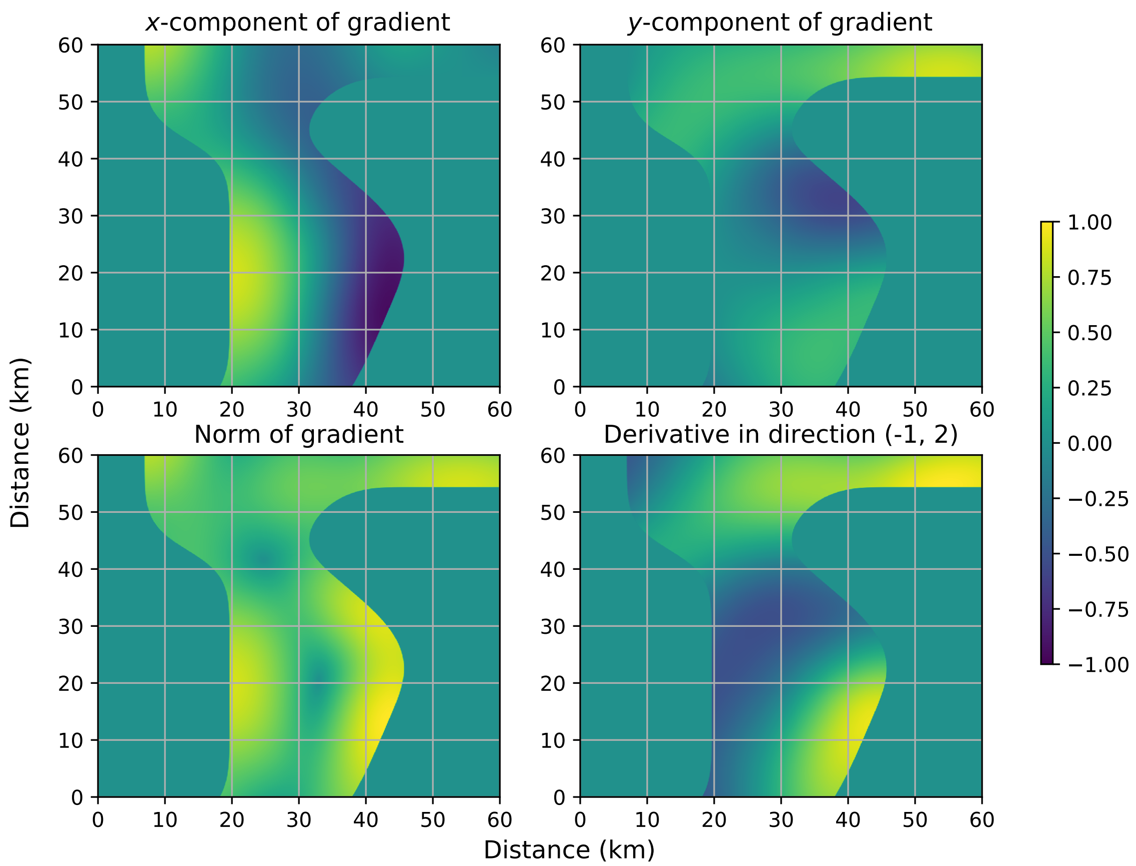


**Figure S2.** Components of the gradient of the simulated topography, in arbitrary units.

The default strength for the topography bias results in a 2 ppm maximum $XCO_2$ anomaly (0.5% of the 400 ppm background). When used in combination with other biases, we reduce the strength to 1.2 ppm (0.3% of the 400 ppm background).

### 1.1.2. Footprint bias

We simulate a column-dependent bias in the data. At the 50 m resolution, we set a bias to linearly increase from -1 at the far left column to 1 at the far right column (arbitrary units). Then, we add noise to each column taken from a uniform distribution between -0.4 and 0.4. We define the strength of the footprint bias to be the strength of this linear trend. In the arbitrary units it is generated in, the strength of the bias is exactly 1. At simulation run-time, we multiply the bias by the desired $XCO_2$ anomaly in ppm. For example, to generate a 0.5 ppm footprint bias, we would multiply the array by 0.5. The small-scale noise mostly averages out for larger pixels, with only small deviations from the linear trend remaining for pixel sizes in the range of $2 \times 2 - 10 \times 10$ km$^2$. Figure S3 shows the final column bias array. The default strength for our simulations is 0.6 ppm, or 0.15% of the 400 ppm background.

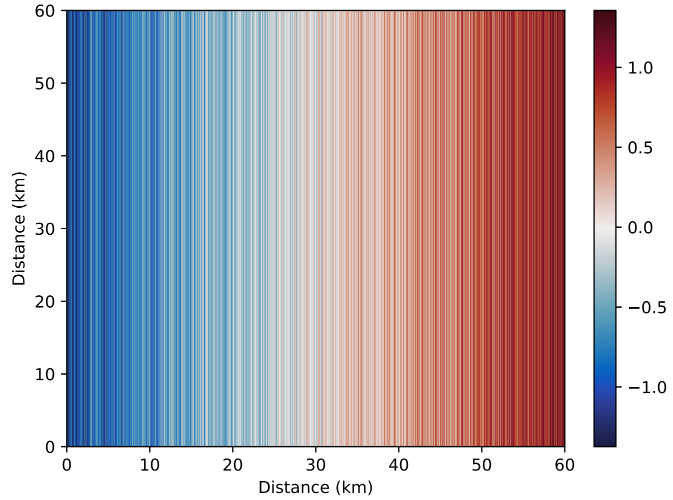


**Figure S3.** Column bias array in arbitrary units.

#### 1.1.3. Cloud mask

Any space-based imaging spectrometer requires clear sky conditions to accurately retrieve $Xco_2$ values. For an instrument with a 60 km wide FoV, we may have the scene partially cloud covered and partially clear. Therefore, we generate a mask such that we only have some observations in the FoV. We use different parameters with the same noise function as for topography, and assign an arbitrary threshold value such that values above this threshold are completely cloudy and values below this threshold are perfectly clear. The resulting mask is shown in Figure S4.

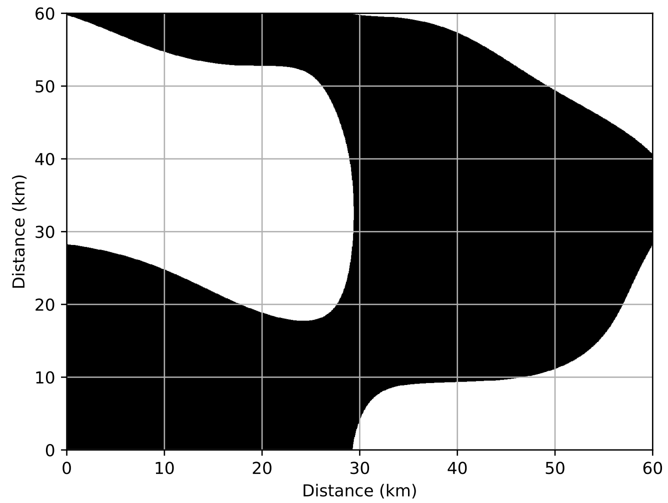


**Figure S4.** Cloud mask. Black represents clear-sky conditions, and white represents cloud cover.

#### 1.1.4. Albedo bias

We wish to simulate a scene with varying albedo that is not accounted for in the retrieval or modelling. We generate another 2D array of correlated noise, and assign arbitrary thresholds so that we have 3 distinct regions. These regions could represent, for example, dense forest cover, bare ground, and grassy fields. These regions are mapped to relative biases of -0.1%, 0%, and 0.1% of the 400 ppm background (equivalent to $\pm$0.4 ppm) . The map is shown in Figure S5.

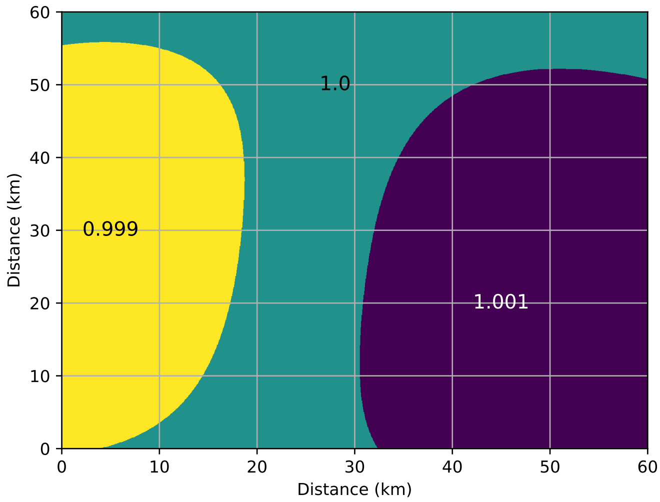


**Figure S5.** Albedo map. The labels 0.999, 1.0, 1and 1.001 show the regions with each bias, respectively.

#### 1.1.5. Swath width

We simulate a narrower swath width than our 60 km wide FoV. We use four swaths, shown in Figure S6. Each swath is 20 km wide, one third the width of the full FoV.

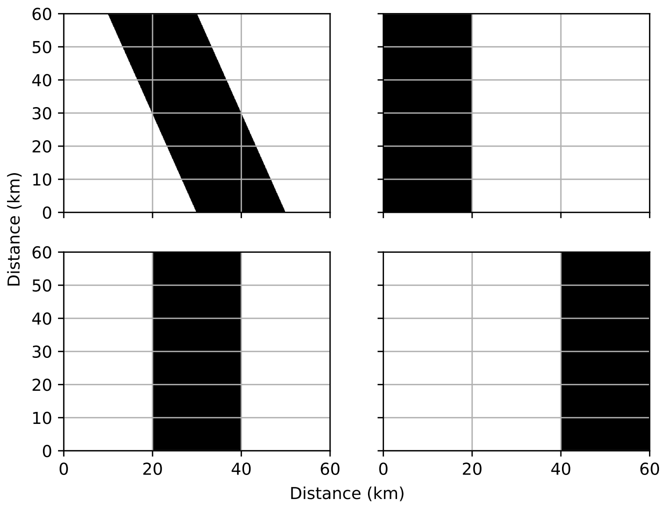


**Figure S6.** Swath masks. Black represents where we have observations, and white represents no observations.

#### 1.1.6. Atmospheric stability

We choose to set the atmospheric stability parameter $a = 130$ when estimating emissions, whereas we use $a_{sim} = 156$ to simulate the enhancements. This means we are trying to fit a plume that is too narrow.

#### 1.1.7. Interfering sources

We simulate adding a second smaller source when simulating the enhancements, and we do not account for this source when carrying out the emission estimates. We use a source with 5 Mt $yr^{-1}$ emissions. The secondary source is slightly offset from the primary source.

### 1.2. Results

Here we present emission estimates from ensembles of 30 simulations for each bias individually. Results are presented as boxplots as in the main text.

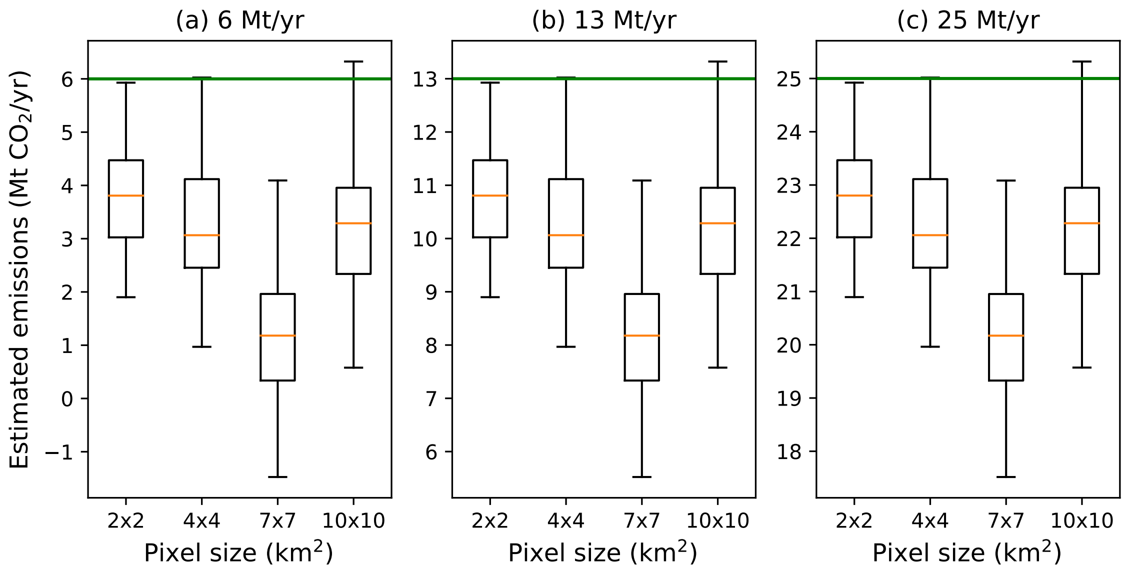


**Figure S7.** Emission estimates for the topography bias (2 ppm bias).

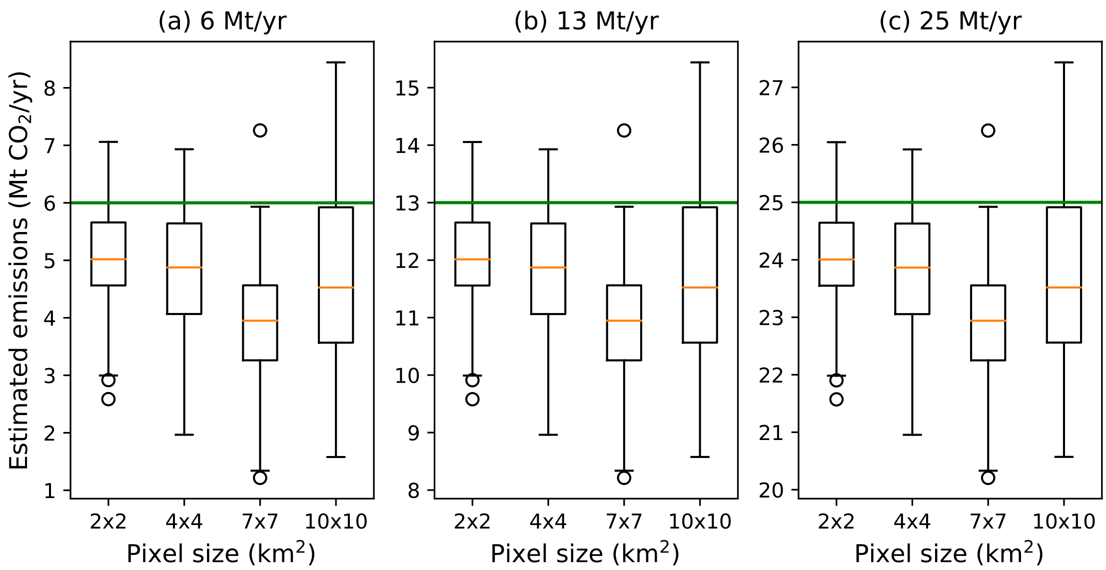


**Figure S8.** Emission estimates for the footprint bias (0.6 ppm bias).

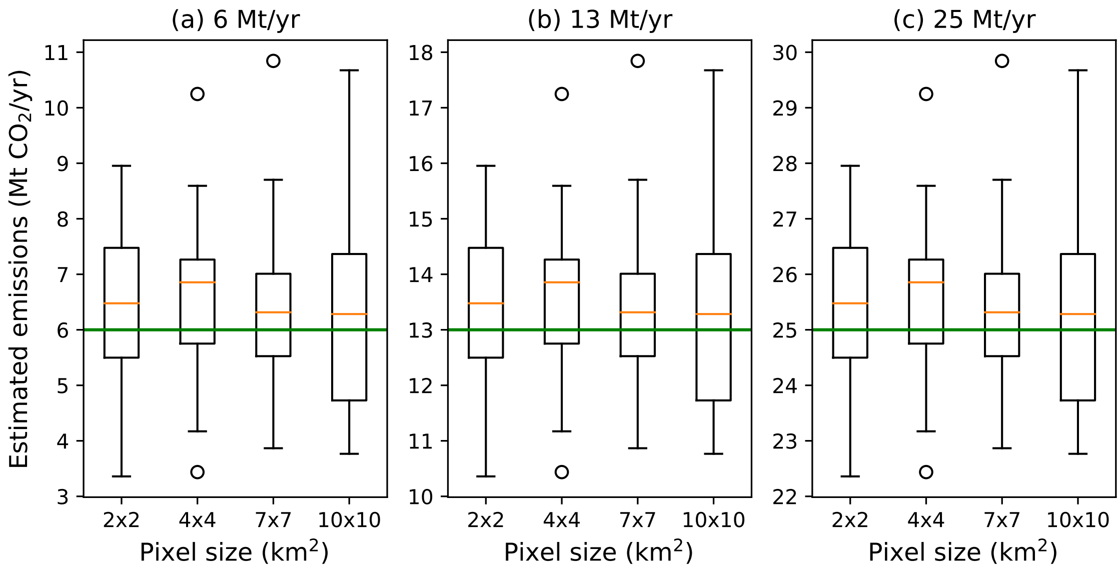


**Figure S9.** Emission estimates for the cloud mask bias.

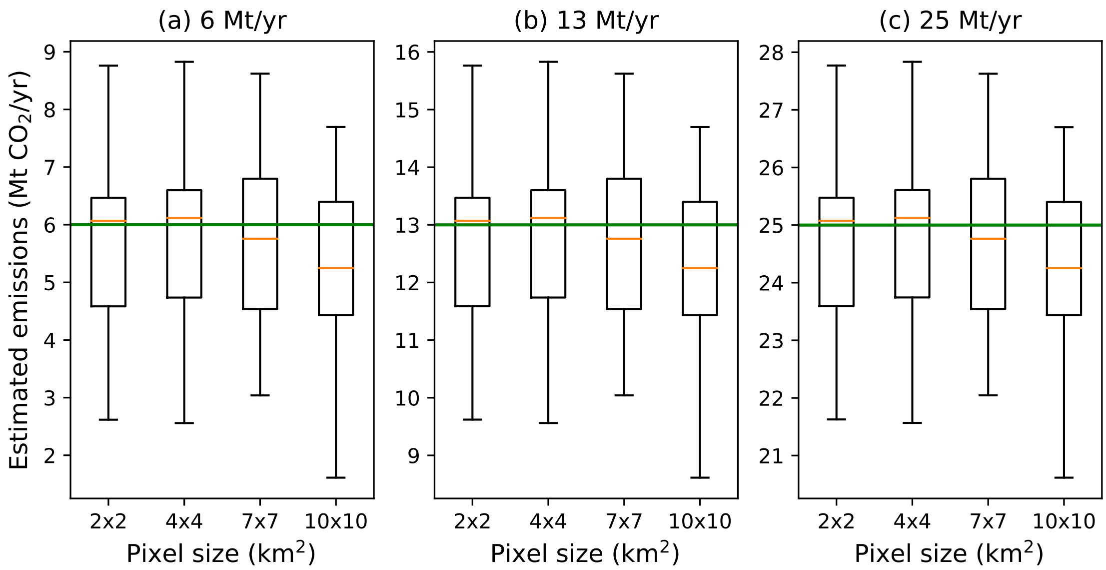


**Figure S10.** Emission estimates for the surface albedo bias ($\pm$ 0.4 ppm bias). The albedo bias (0.4 ppm) is quite weak compared to the noise, and so the results are not very sensitive to the presence of the bias. However, we can see a larger variation in the $2 \times 2$ $km^2$ emission estimates than in the base case.

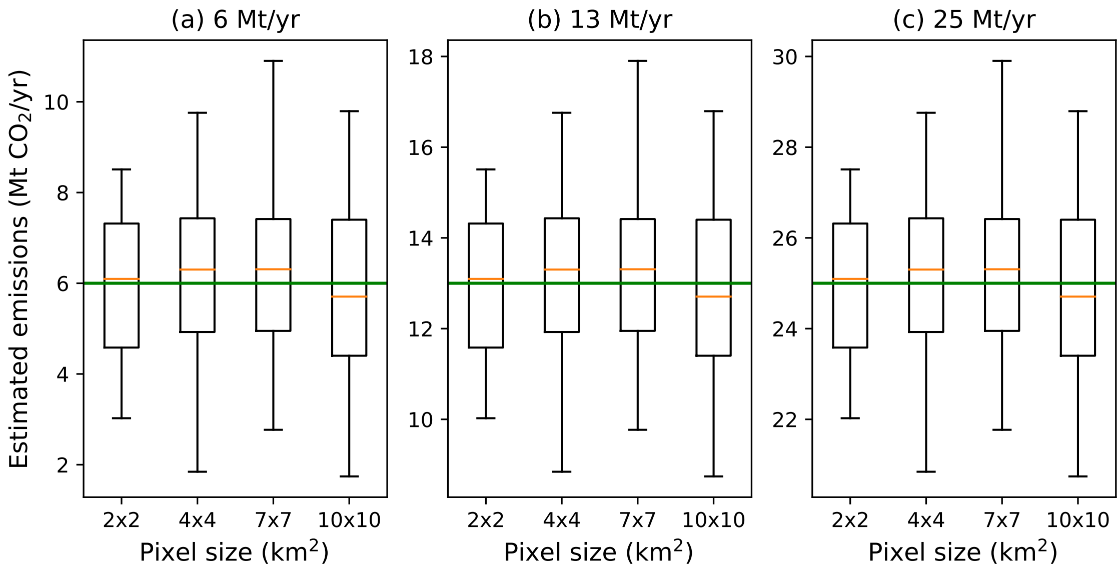


**Figure S11.** Emission estimates for left swath mask.

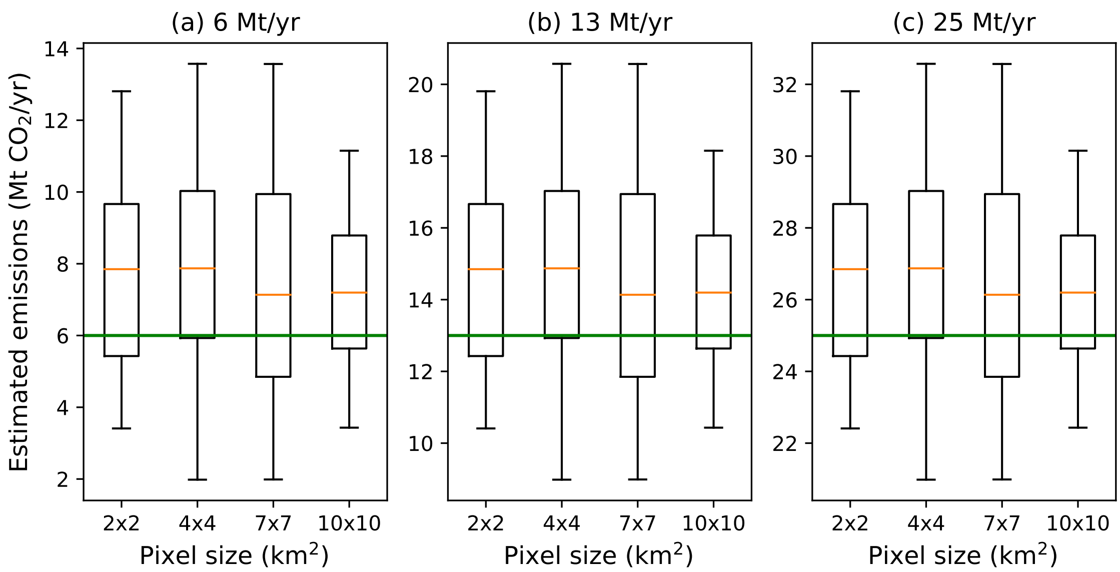


**Figure S12.** Emission estimates for diagonal swath mask.

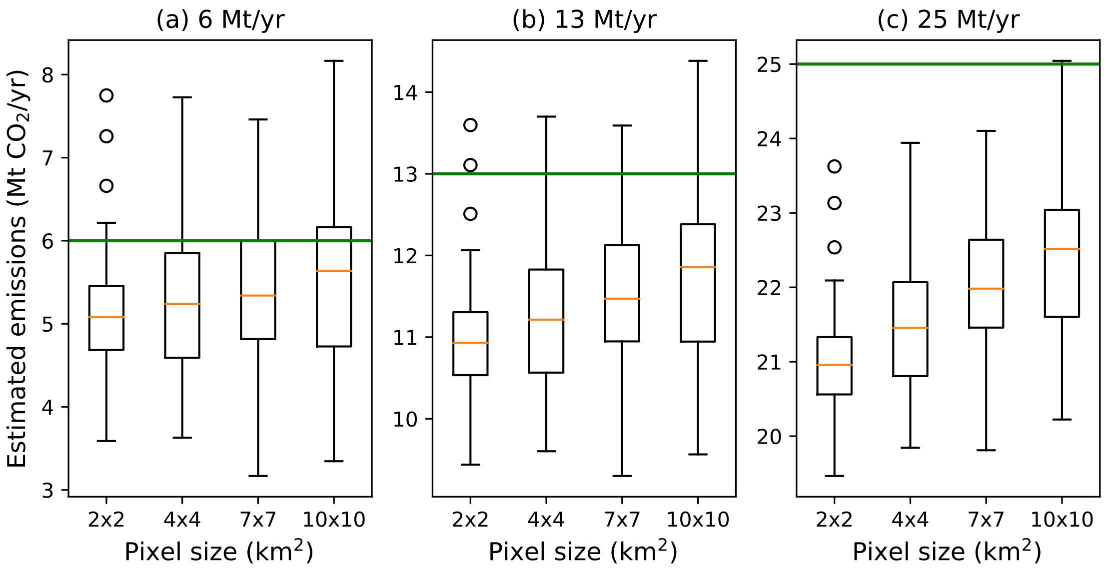


**Figure S13.** Emission estimates when assuming an incorrect atmospheric stability parameter, $a = 130$, when the data was generated with $a = 156$.

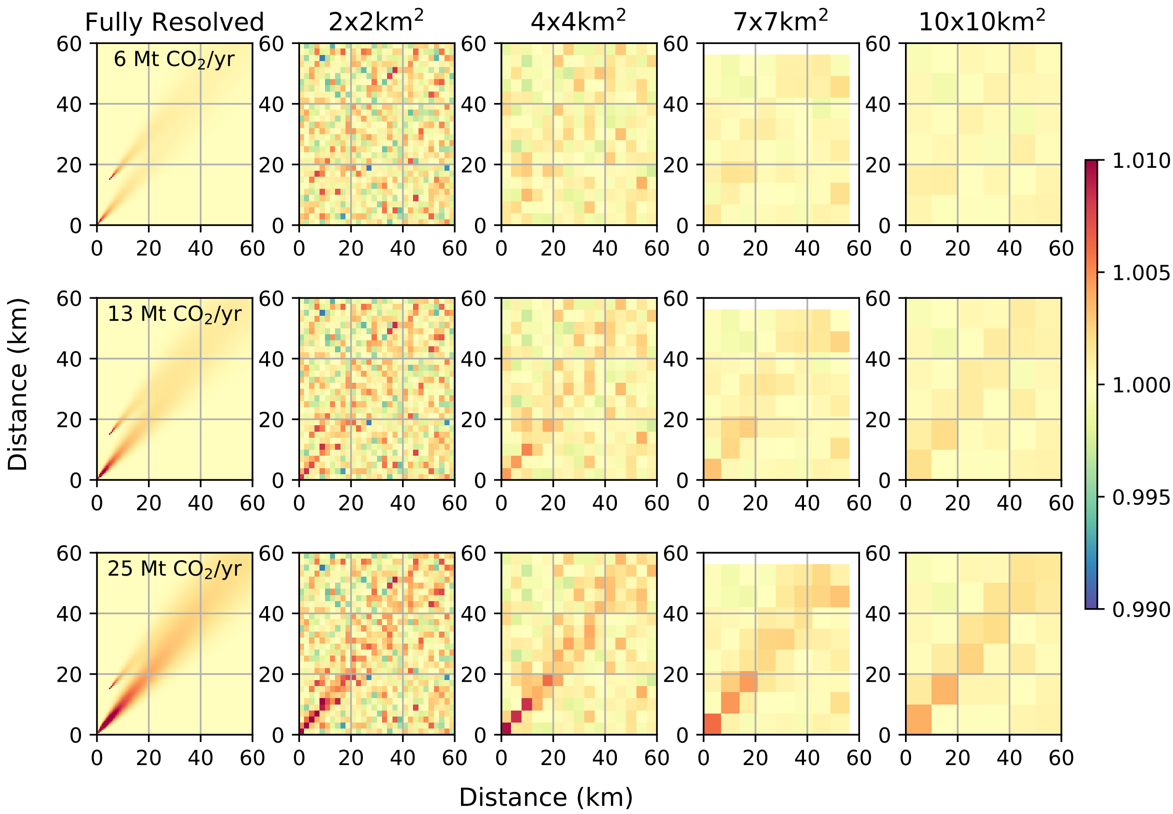


**Figure S14.** Simulated $XCO_2$ observations relative to 400 ppm background with a weak (5 Mt yr$^{-1}$ interfering source in the FoV that is not accounted for in the least squares fit when estimating emissions.

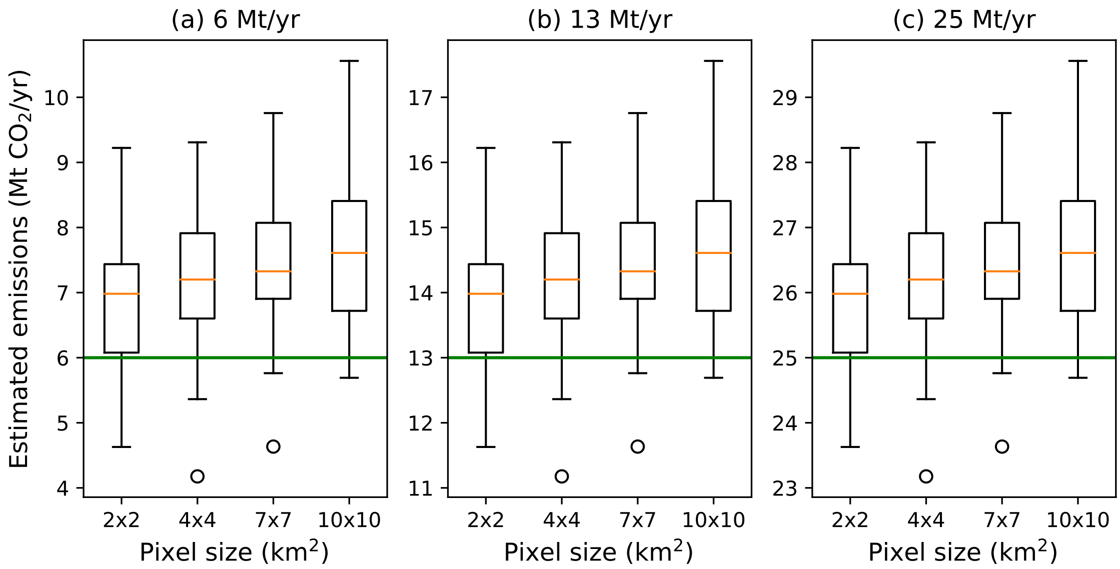


**Figure S15.** Emission estimates with a weak 5 Mt yr$^{-1}$ source in the FoV that is not accounted for in the least squares fit when estimating emissions.

59 ## 2. Daily emissions variability

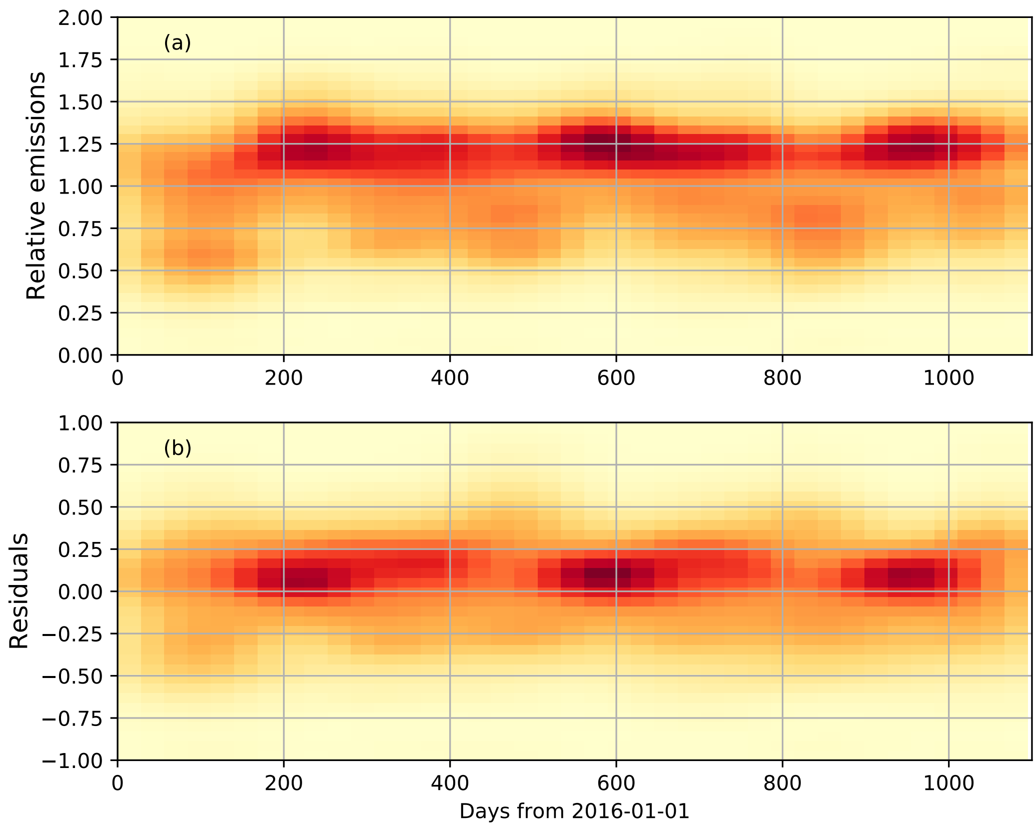


**Figure S16.** 2D histograms of relative daily emissions for 50 highest emitting US power plants for 2016—2018. **a** Relative daily emissions with no seasonality removed. **b** Residual between emissions after removing weekly cycle and mean emissions, normalized by mean emissions.

## References

1. Kiel, M.; O'Dell, C.W.; Fisher, B.; Eldering, A.; Nassar, R.; MacDonald, C.G.; Wennberg, P.O. How bias correction goes wrong: measurement of $XCO_2$ affected by erroneous surface pressure estimates. *Atmospheric Measurement Techniques* **2019**, *12*.