

Data Drought in the Humid Tropics: How to Overcome the Cloud Barrier in Greenhouse Gas Remote Sensing

C. Frankenberg^{1,2}, Y. M. Bar-On¹, Y. Yin³, P.O. Wennberg^{1,4}, D.J. Jacob⁵,
A.M. Michalak^{6,7}

¹Division of Geological and Planetary Sciences, California Institute of Technology, Pasadena, California, USA

²Jet Propulsion Laboratory, California Institute of Technology, Pasadena, California, USA

³Department of Environmental Studies, New York University, New York, New York, USA

⁴Division of Engineering and Applied Science, California Institute of Technology, Pasadena, California, USA

⁵School of Engineering and Applied Science, Harvard University, Cambridge, Massachusetts, USA

⁶Carnegie Institution for Science, Stanford, California, USA

⁷Department of Earth System Science, Stanford University, Stanford, California, USA

Key Points:

- Data yields of current remotely-sensed greenhouse gas (GHG) missions in the humid tropics are often below 1%.
- Shallow cumulus clouds cause most of the low data yields, esp. in the wet season.
- Spatial resolution finer than 500 m can overcome the data sparsity in the tropics

Corresponding author: Christian Frankenberg, cfranken@caltech.edu

Corresponding author: Yinon M. Bar-On, ybaron@caltech.edu

Abstract

Diagnosing land-atmosphere fluxes of carbon-dioxide (CO_2) and methane (CH_4), is essential for evaluating carbon-climate feedbacks. Greenhouse gas satellite missions aim to fill data gaps in regions like the humid tropics, but obtain very few valid measurements due to cloud contamination. We examined data yields from the Orbiting Carbon Observatory alongside Sentinel 2 cloud statistics. We find that the main contribution to low data yields are frequent shallow cumulus clouds. In the Amazon, the success rate in obtaining valid measurements vary from 0.1% to 1.0%. By far the lowest yields occur in the wet season, consistent with Sentinel 2 cloud patterns. We find that increasing the spatial resolution of observations to ~ 200 m would increase yields by 2-3 orders of magnitude, and allow regular measurements in the wet season. Thus, the key effective tropical greenhouse gas observations lies in regularly acquiring high-spatial resolution data, rather than more frequent low-resolution measurements.

Plain Language Summary

Our research looks at how well satellites are able to observe greenhouse gases such as carbon dioxide and methane in tropical areas, which is important for understanding climate change. We find that these satellites often cannot make good measurements in places like the Amazon rainforest due to clouds. By using space-based instruments that can peek in between clouds (requiring about 200-300 meters spatial resolution), we would get much more frequent information, even during the rainy season. Our study shows that it's better to have high-spatial resolution, detailed satellite data regularly rather than more frequent lower resolution observations that do not yield usable measurements.

1 Introduction

While in situ measurements of greenhouse gases provide the most accurate benchmark (Komhyr et al., 1985; Andrews et al., 2014), they cannot provide spatially dense global coverage. Remotely sensed observations can't match the accuracy of in-situ measurements; however they offer the potential to provide dense spatial coverage, especially in regions where in situ measurements are limited. In the tropics, space-based measurements could enable substantial knowledge gains, as the tropics are not only sparsely sampled by in situ observations but also essential to global carbon budgets.

49 The tropics are, however, much more cloudy, and these clouds obscure the view from
50 space. In passive optical remote sensing of Earth’s atmosphere and surface, clouds shield
51 the lower atmosphere and affect photon path-length distributions, greatly complicating
52 the retrieval of greenhouse gas concentrations. This issue is particularly challenging due
53 to the stringent accuracy and precision requirements for greenhouse gas observations (Miller
54 et al., 2007; Merrelli et al., 2015). Consequently, rigorous cloud filtering is necessary, al-
55 beit at the cost of reducing the fraction of usable observations. Understanding the trade-
56 off between cloud filtering and data usability is vital for assessing the scientific value of
57 space-borne missions.

58 To alleviate the impact of clouds, the Orbiting Carbon Observatory (Crisp et al.,
59 2004) utilises a pushbroom technique featuring a narrow cross-track swath width of 10 km
60 and a spatial resolution of 1.29 km cross-track and 2.25 km along-track, which is finest
61 resolution among existing missions targeted at atmospheric greenhouse gases. While this
62 fine resolution was chosen to provide sufficient data even in the tropics, data yield pre-
63 dictions were based on cloud climatologies (Rayner et al., 2002) based on AVHRR data
64 (James & Kalluri, 1994) aggregated to coarser scales (Stowe et al., 1999), and ignored
65 3D effects in the vicinity of clouds (Massie et al., 2017, 2022). The impact of small clouds
66 ranging from tens to a few hundred meters was thus not fully captured.

67 Here, we revisit the impact of clouds on GHG remote sensing by quantifying long-
68 term OCO-2 data yields. These findings are compared against cloud-free probabilities
69 computed from 4 years of Sentinel 2 cloud data at 10 m resolution. This comparison helps
70 us explore ways to improve the disappointing data collection from tropical regions in cur-
71 rent satellite missions in the design of the next generation of satellites focused on space-
72 based observations of greenhouse gases.

73 **2 Materials and Methods**

74 To assess the impact of clouds on greenhouse gas (GHG) remote sensing, we uti-
75 lize data from the OCO-2 and OCO-3 missions (Wunch et al., 2017; Taylor et al., 2020)
76 for actual GHG measurements and Sentinel 2 for cloud observations (Tarrío et al., 2020).
77 OCO-2 and Sentinel 2 are on sun-synchronous orbits with an overpass time around 1:30pm
78 and 10:30am, respectively. OCO-3 is hosted on the ISS with a precessing orbit, thus over-
79 pass times vary, enabling measurements from early morning to late afternoon (see Text

80 and Figure S2). We find that overpass times matter somewhat, as OCO-3 data yields
81 at the Sentinel 2 overpass time are almost a factor two higher than for the OCO-2 over-
82 pass time. Thus, the time-of-day explains some of the discrepancies between Sentinel 2
83 statistics and OCO-2 observed data yields noted below.

84 We analyze OCO-2 (v11r) and OCO-3 (v10r) data to determine the number of high
85 quality GHG measurements, applying the 'xco2_quality_flag = 0' for accuracy. We cal-
86 culate total number of measurement counts using the OCO-2's L1b files which provide
87 a total count of the number of observations downlinked from the spacecraft. For global
88 spatially-resolved data yields, we use the ratio of high quality (passing the quality fil-
89 ter) to total measurements.

90 Cloud statistics at coarse scales, such as those provided by MODIS, are insufficient
91 for our analysis. Even small cloud fractions within a greenhouse gas measurement's foot-
92 print can significantly impact data quality, and are often missed by cloud climatologies.
93 One reason for this is the stark surface albedo contrast between the O₂ A-band (about
94 0.4-0.5 at 760 nm) and the GHG bands (as low as 0.05 at 1.6 or 2.3 μm). Thus, a cloud
95 with an albedo of 0.5 covering only 1% of a footprint can contribute 10% of the signal
96 to the GHG bands but only 1% in the reference oxygen band. If this cloud shields 10%
97 of the column (about 1 km cloud height), it can cause a low bias of 1% in retrieved gas
98 concentrations. Thus, requiring a $<$ ppm bias might require screening of scenes with $<$
99 0.2% fractional cloud cover. This drives our stringent 0.2% cloud fraction thresholds in
100 the tropics.

101 To study the impact of clouds on OCO-2, we thus have to obtain cloud statistics
102 at a much finer resolution than OCO-2's footprint. In the tropics, frequent shallow cu-
103 mulus clouds are often linked to forest surface fluxes (Heiblum et al., 2014), are spatially
104 organized and have cloud gaps that are smaller than 1 km in scale. Sentinel 2, with its
105 frequent revisits and 10m resolution (Drusch et al., 2012), is uniquely suited for this task.
106 It enables us to accurately calculate the likelihood of obtaining cloud-free measurements.
107 In our analysis, a 'cloud free' pixel is one where less than 0.2% of the footprint area is
108 covered by clouds or cloud shadows. We employ the Cloud Score+ product (Pasquarella
109 et al., 2023) based on Sentinel 2 data, using a threshold of 0.65 to identify cloud-free pix-
110 els. The analysis is performed using Google Earth Engine, focusing on specific latitude
111 and longitude ranges and using square-sized convolution kernels to vary spatial resolu-

112 tions. Within each $1^\circ \times 1^\circ$ degree area, we compute the fraction of pixels passing our cloud
 113 filter threshold at a given footprint size for each individual Sentinel-2 image, which are
 114 acquired every five days. All individual cloud-free fractions per image are then used to
 115 compute probability distributions of cloud-fractions within a certain domain and time-
 116 period.

117 3 Results

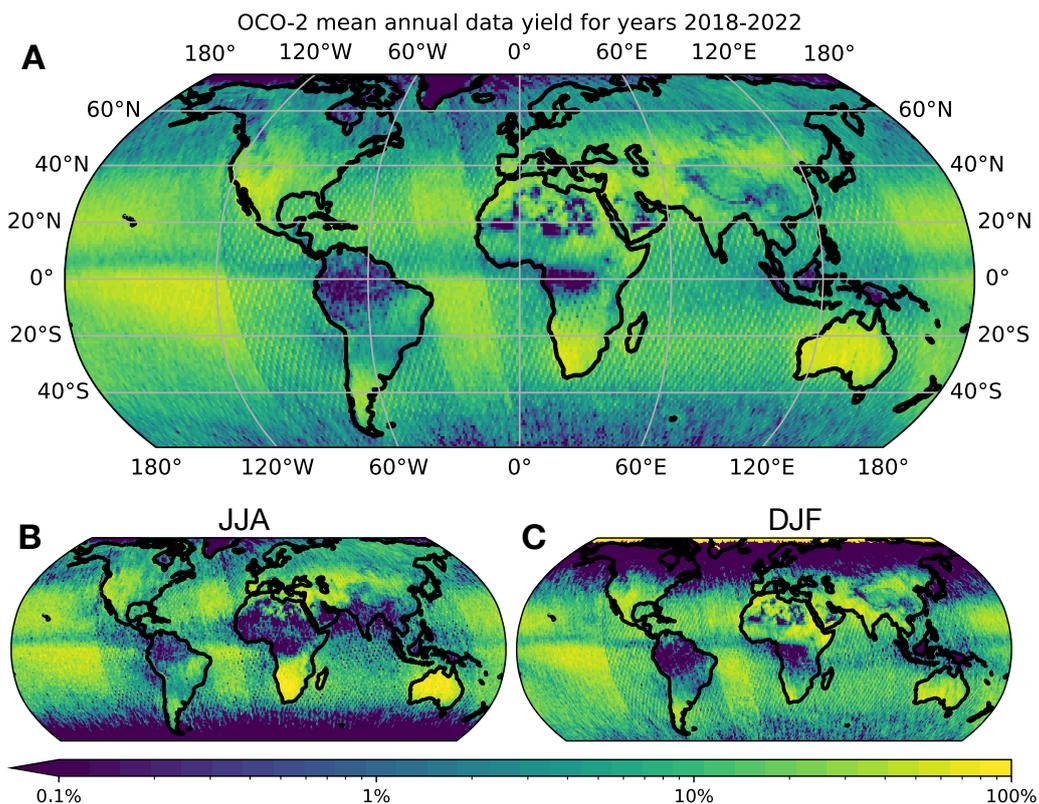


Figure 1. A) The data yield from OCO-2 within $1^\circ \times 1^\circ$ boxes from 2018 through 2022 on a logarithmic scale. Bottom row: Seasonal average for June/July/August (B) and December/January/February (C). The data yields vary by three orders of magnitude, with by far the lowest over areas with tropical rainforests.

118 Figure 1 illustrates the stark geographic variation in OCO-2 data yield based on
 119 four years of data, revealing significant disparities spanning three orders of magnitude.
 120 In humid tropical areas, data yield frequently falls below 1%, especially during the wet
 121 season. Conversely, most other global regions consistently show yields above 5%, apart

122 from some spurious regions in the Sahara, which don't pass the OCO-2 quality flag for
123 unrelated reasons, likely due to brightness threshold used in OCO-2 filtering. On sea-
124 sonal time-scales the largest changes are due to varying solar zenith angles at high lat-
125 itudes and movement of the ITCZ in the tropics.

126 Other peculiar patterns appear over the oceans, as orbit tracks that are predom-
127 inantly over the oceans are almost exclusively performed in the glint observation mode,
128 which has much higher data yields over dark oceans. OCO-2's orbits have a repeat cy-
129 cle of 16 days, which means that a location with a 0.2% data yield would essentially never
130 be observed (i.e., less than once every 20 years). This represents a dramatic discrepancy
131 between potential and actual revisit times in the humid tropics. While OCO-2 can the-
132 oretically monitor tropical fluxes (Liu et al., 2017), the reliance on measurements from
133 data-rich surrounding areas and from rare clear-sky conditions can introduce systematic
134 biases when attempting to infer carbon fluxes with inverse analyses.

135 For the TROPOMI methane product (Hu et al., 2016), similar reductions in data
136 yields have been observed, spanning more than three orders of magnitude (Qu et al., 2021).
137 TROPOMI's larger footprint of 5-7 km allows a wide swath and daily revisit times, but
138 might at the same time explain the even lower data yields. Thus, OCO-2 and TROPOMI
139 data yields raise questions about the effectiveness of frequent km-scale resolution obser-
140 vations in data-sparse tropical regions.

141 The humid tropics show the worst data yields but are arguably the most impor-
142 tant place for observing the global carbon cycle, as they have the highest above-ground
143 carbon stocks (Santoro et al., 2020) and natural methane emissions (Saunois et al., 2020).
144 To obtain more reliable flux estimates across major tropical areas and, more importantly,
145 to capture spatial variations within the heterogeneous major tropical basins, higher data
146 density both spatially and temporally is key. Towards that goal, we have to evaluate why
147 the current missions have such low data yields and how we can mitigate this shortcom-
148 ing.

149 To quantify the role of clouds on data yields, we derive probabilities of cloud-free
150 satellite footprints at varying footprint resolutions using Sentinel-2 data. Due to com-
151 putational demands, we focused on the tropics, the areas with the lowest data yields in
152 OCO-2, OCO-3, TROPOMI, and GOSAT (Yokota et al., 2009).

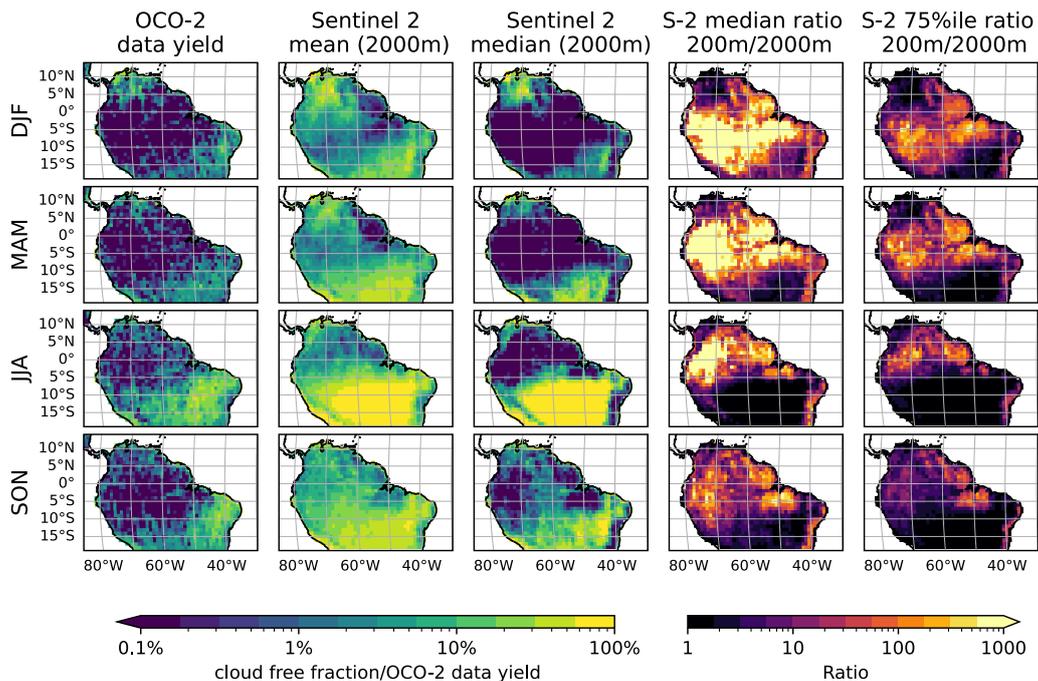


Figure 2. OCO-2 data yields and Sentinel-2 cloud statistics in South America. The rows show seasonal variations individually averaged over three months, while the columns show the mean OCO-2 data yield, the mean and median cloud free fraction at a spatial footprint of 2 km, and the ratio of the median and 75-percentile cloud-free fraction for a spatial footprint of 200 m vs. 2000 m.

153 Figure 2 shows the seasonal variations of OCO-2 data yields and Sentinel-2 cloud
 154 statistics in the Amazon region (see SOM for other areas). There are strong spatial and
 155 temporal commonalities between the OCO-2 data yields and the cloud statistics, con-
 156 firming that clouds are a major contributor to yield reductions. A striking feature is the
 157 difference between the mean and median of cloud-free probabilities for a 2 km pixel size.
 158 This is especially true within the Amazon basin, where the mean can be more than an
 159 order of magnitude higher than the median. A 200 m resolution would increase the me-
 160 dian of the cloud-free likelihoods by 2-3 orders of magnitude compared to 2 km pixels.
 161 The 75 percentile would increase by 1-2 orders of magnitude. Overall, it appears that
 162 OCO-2 obtains fewer valid measurements than we would expect just on the basis of clouds,
 163 missing out on the occasional cloud-free scenes that contribute dis-proportionally to the
 164 mean. It may be related to the challenge that tropical rainforests are much darker in the
 165 CO₂ bands at 1.6 and 2 μ m. For instance, there are large areas below 5 degrees south

166 in June/July/August, with relatively cloud-free conditions yet unexpectedly low OCO-2
 167 2 data yields, warranting further investigations into the filter criteria employed by the
 168 OCO missions. In general, the OCO-2 yields are often more similar to the median of our
 169 cloud statistics. While time-of-day of our cloud statistics (10:30am) vs. OCO-2 (1:30pm)
 170 might be a reason for worse yields in OCO-2, it does not fully explain the discrepancies
 171 (see Text and Figure S2).

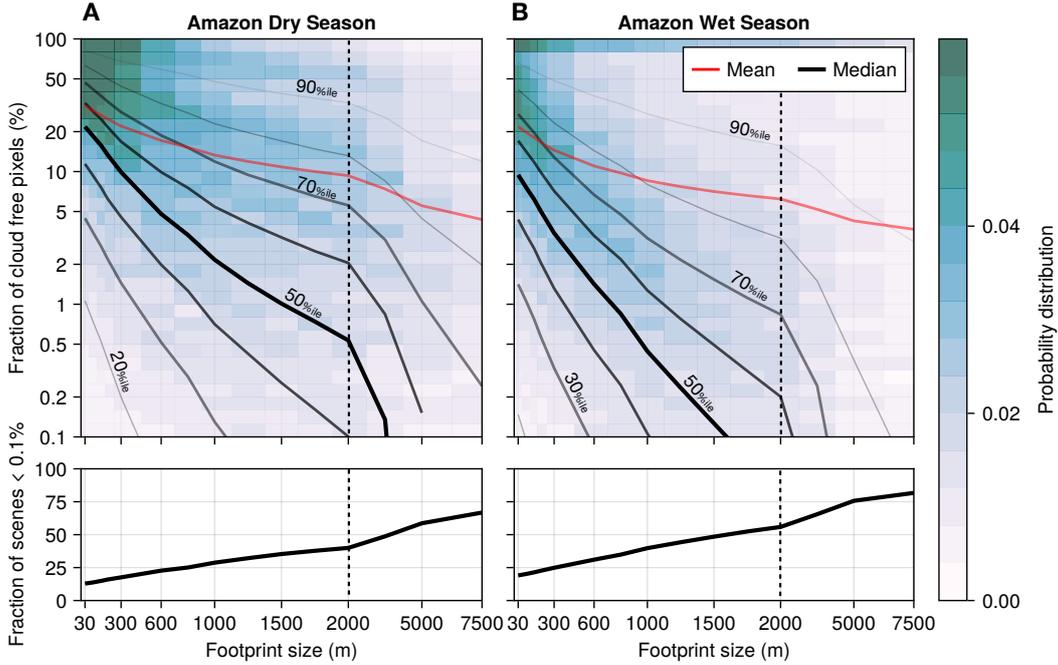


Figure 3. Frequency distribution of the fraction of cloud-free scenes for the dry (left, July through September) and wet (right, December through May) season within the Amazon (70W-60W; 2S-2N)]. Note the scale break at 2 km. The distribution on a log-scale as a function of footprint size is shown color-coded on the top row, with the percentiles (median as thick line, including 10th percentile steps with decreasing thickness) and the mean shown as lines. Towards larger footprints, the distribution gets more skewed, especially during the wet season, where the mean and 90th percentile lines intersect at around 5 km footprint size. The bottom row shows the fraction of scenes that had less than 0.1% cloud free pixels, reaching 80% in the wet season at a pixel size of 7.5 km.

172 A peculiar feature in the Amazon is the extreme skewness of cloud free likelihood
 173 distributions, while the mean and median are closer to each other outside the Amazon
 174 basin, and when yields are higher in general. The much higher mean indicates that a few

175 large-scale cloud-free events contribute disproportionately to overall data yields. The me-
176 dian, however, is more indicative in how likely each satellite overpass is of exceeding a
177 cloud-free fraction, i.e. there is a 50% chance of observing a higher cloud free fraction
178 than the median.

179 In Figure 3, we show the probability distribution of obtaining cloud free pixels (on
180 a logarithmic scale) as a function of footprint size in the dry and wet season, respectively.
181 In the dry season, there is a probability peak at high cloud-free fractions, consistent across
182 all footprint sizes. In the wet season, the peak at large cloud-free fractions diminishes
183 and a peak around 5-30% likelihoods appears at smaller footprints, moving towards 0.5%
184 at 2 km footprint size. The median drops by two orders of magnitude moving 30 m to
185 2 km footprints. In both seasons, the mean and median diverge with footprint size. In
186 the wet season, the mean intersects the 90th percentile at 5 km footprint size, underlin-
187 ing that rare events dominate the mean with increasing pixel size. Also, there are a few
188 scenes available with very high cloud free fractions, likely caused by large-scale subsi-
189 dence. These few scenes contribute substantially to the mean data yield, which decays
190 much less with footprint size than the median or the percentiles. In addition, some of
191 the regions where the ratio in the median and 75%ile is not as enhanced in the middle
192 of the Amazon in Figure 2 are associated with rivers or open water, which can cause large-
193 scale subsidence and cloud-free scenes but which are dark in the nadir observation ge-
194 ometry. Thus, some of these scenes might be filtered out in OCO-2 because of the lack
195 of reflected light from open water surfaces.

196 In principle, we can leverage the finding that smaller footprint sizes can dramati-
197 cally increase the fraction of cloud free pixels. However, smaller pixels will be more noisy
198 and limit the theoretical revisit time in the absence of clouds, as it is harder to feature
199 a wide swath while having small pixels. As long as measurements are photon shot noise
200 limited, however, the noisiness of individual pixels is less of a concern, as we can aggre-
201 gate valid pixels. In this case, aggregating valid smaller pixels within a larger domain
202 to cover an integrated surface area of $2 \times 2 \text{ km}^2$ will have the same precision as one sin-
203 gular cloud-free measurement at $2 \times 2 \text{ km}^2$ footprint size within that larger domain. In the
204 case of shallow cumulus cloud fields, many small pixels within cloud gaps can be aggre-
205 gated while almost all large-footprint measurements will have failed due to fractional cloud
206 cover. Thus, the increase in data yield with footprint size strongly depends on the spa-

207 tial scales of clouds and gaps in between, which can be highly structured in tropical forests
 208 (Heiblum et al., 2014).

209 Thus, a hypothetical instrument that averages measurements over a given surface
 210 area will have the same precision irrespective of footprint size. If we define a threshold
 211 for the cloud free fraction that enables enough measurements within a larger geographic
 212 domain, we can derive how often and how evenly spaced in time an area will be observed
 213 depending on the footprint size. Here, we chose a 2% cloud fraction cutoff, which is equiv-
 214 alent to a single 2000 m footprint pixel within a 20x10 km² domain.

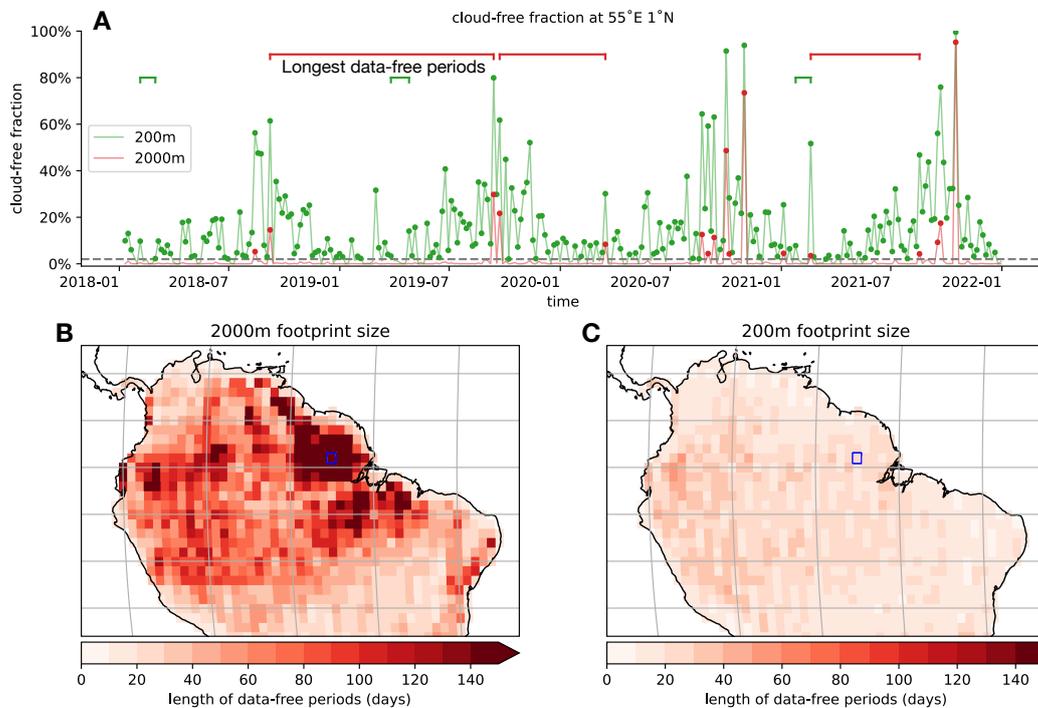


Figure 4. A) Time series of the cloud-free fraction of individual Sentinel-2 images (every 5 days) for a 200 m and 2000 m footprint resolution. Dots mark scenes that exceed the 2% threshold and the bars outline the longest three periods without any valid data acquisitions passing this threshold. B) Map of the average of the three longest data-free periods at 2000 m footprint size (in days). C) as B) but for 200 m footprints, 5-10 times shorter than for 2000 m. At smaller footprint sizes, more data is acquired over and spaced over more regular time intervals, even in the wet season.

215 The skewness in the cloud statistics already hinted at the fact that rare events dom-
216 inate the mean at coarser spatial resolutions, while most observations have much lower
217 cloud free scenes. This should increase the time-period in between useful measurements.
218 Figure 4 shows a time-series of cloud free fractions computed from individual Sentinel-
219 2 images within a 1x1 degree area in the Amazon. The very skewed distribution at 2000 m
220 footprint size can be observed: Most scenes are below the 2% cutoff and many that pass
221 the threshold have very high cloud free fractions, indicating the absence of broken cloud
222 fields. At 200 m footprint size, the distribution of the cloud-free fraction is more evenly
223 distributed and no long periods devoid of any useful measurements exist. Panels B-C
224 show the average length (in days) of the three longest data-free periods at 2000 m and
225 200 m resolution, respectively. The data free periods (at 2000 m) exceed 150 days in many
226 regions within the Amazon, even if sampled every 5 days as Sentinel 2 does. Thus, it ap-
227 pears unlikely that even daily revisit times in the Amazon at coarse spatial resolution
228 would provide shorter data-free periods. Somewhat contrary to intuition, the key to ob-
229 serving the humid tropics more frequently is thus not to have more frequent measure-
230 ments but to have finer spatial resolution (see also Fig. S3 for the trade-off between re-
231 visit times and footprint sizes). Given the importance of the tropics for GHG fluxes and
232 the currently poor revisit times for valid measurements in these regions, prioritizing high
233 resolution greenhouse gas measurements is needed.

234 **4 Discussion and Conclusions**

235 To minimize the impact of prior assumptions on estimation of GHG fluxes, inverse
236 methods require dense measurements in both space and time. In the tropics, in situ ob-
237 servations are very sparse and provide motivation for using remote sensing from space
238 to fill in the gaps. To date, however, GHG missions have had little success in observing
239 CO₂ and CH₄ above tropical forests, with the fraction of valid retrievals varying over
240 space and time and being as low as 0.1% during the wet season.

241 Using Sentinel 2 data at 10 m resolution, we illustrate that the Achilles heel of trop-
242 ical remote sensing of GHGs is clouds. For example, at the footprint size of OCO-2, we
243 find that the likelihood of obtaining a cloud-free satellite footprint is low and the dis-
244 tribution of likelihoods is highly skewed. Generally, both large-scale cloud systems or shallow-
245 cumulus cloud fields reduce the likelihood of observing cloud-free scenes by several or-
246 ders of magnitude, such that most satellite orbits passing the humid tropics yield almost

247 no measurements. Periodically, however, the observations coincide with large-scale sub-
248 sidence, suppressing clouds and contributing most of the valid measurements; this, in turn,
249 might bias the flux inversion. Thus, mean data yields can hide the fact that there can
250 be prolonged data-free periods.

251 The choice of equator crossing time also plays a role in limiting data. While con-
252 vective systems and their associated clouds typically follow solar heating – increasing in
253 the late morning and peaking in the early to late afternoon, our analysis with time-of-
254 day resolved statistics from the OCO-3 mission, suggests maximum data yield just be-
255 fore mid-day likely because the lower solar zenith angle reduces the spatial domain through
256 which the direct light-path traverses and lowers the amount of shading in between the
257 clouds (Text and Figure S2).

258 What spatial resolution is ideal for measurements in the tropics? Even though data
259 yields improve with smaller pixel size, the revisit time increases, thereby offsetting some
260 of the benefit of the high spatial resolution. We find that footprint sizes around 200-400 m,
261 can optimize coverage and revisit times, potentially solving the data-drought problem
262 in the humid tropics (Figure and Text S3).

263 To improve greenhouse gas remote sensing in the tropics in the future, we need dra-
264 matically increase the amount of measurements that are not impacted by clouds. Thus,
265 we need either more cloud-free observations or use algorithms that are less sensitive to
266 fractional cloud cover. For cloud-avoidance, better spatial and temporal sampling requires
267 much better spatial resolution than currently available. How can we leverage that find-
268 ing? Obtaining high spatial and spectral resolution using passive spectroscopy is diffi-
269 cult, but recent studies have shown that very high spectral resolution is not necessar-
270 ily required (Cusworth et al., 2019; Jongaramrungruang et al., 2021; Wilzewski et al.,
271 2020; Galli et al., 2013). In terms of algorithm choices, a major complication for the op-
272 erational OCO-2 retrievals is that the contrast between cloud and surface albedo within
273 the O₂ A-band and the CO₂ bands is very different. As the radiative transfer forward
274 model requires horizontal homogeneity, sub-pixel clouds violate that requirement and
275 can thus be very sensitive to fractional clouds, as the relative contribution from clouds
276 to back-scattered light will be much higher in the CO₂ bands. For complex retrieval meth-
277 ods that rely on a separate oxygen band to constrain the light-path distribution, this can
278 be critical. Methods that can use a proxy gas for light path referencing within the same

—or nearby— wavelength window as the target gas of interest avoid that problem. Thus, these methods are less sensitive to clouds and can make use of simpler radiative transfer schemes. Such a proxy retrieval has been successfully implemented with SCIAMACHY, which measured at 1.35 nm FWHM (Frankenberg et al., 2005) and yields results comparable to more complex algorithms (Schepers et al., 2012). Similarly, a proxy retrieval substantially increased data yields in the tropics for the GOSAT mission (Parker et al., 2020) as cloud filters could be relaxed. However, these methods so far rely on CO₂ measurements as a proxy gas; thus, a different proxy gas would be required to constrain CO₂ itself. N₂O could be a viable alternative as it varies much less in the troposphere than either CH₄ and CO₂ and has absorption features in the vicinity of the strong CO₂ and CH₄ bands within the 2-2.4 μm range. Active systems with small footprint are also possible, especially as they observe in a true nadir geometry, both for illumination and receiver, eliminating cloud shadows and maintaining a constant viewing geometry across the globe. Lidar observations thus provide another path forward, as the laser pulses typically have footprints of less than 100 m, thus also being able to observe in between clouds or over fully cloudy pixels, as this fine spatial resolution greatly reduces horizontal heterogeneity in both surface and cloud properties (Ramanathan et al., 2015; Ehret et al., 2017; Mao et al., 2018). In essence, small ground pixels are key for solving the data drought in the humid tropics. They offer the additional advantage of observing stronger spatial concentration gradients in greenhouse gases, which improves flux inversions.

5 Open Research

5.1 Data Availability Statement

All datasets used in this manuscript are publicly available and archived either through NASA data centers or Google Earth Engine. OCO-2 and OCO-3 XCO₂ lite files are available from the DAAC archive (OCO-2/OCO-3 Science Team, Payne, & Chatterjee, 2022; OCO-2/OCO-3 Science Team, Chatterjee, & Payne, 2022). OCO-2 and OCO-3 L1b files are available from the same DAAC (OCO-2 Science Team et al., 2022, 2022). Cloud identification data based on Sentinel 2 are obtained through the Cloud Score+ product (Pasquarella et al., 2023), publicly available as Image collection at https://developers.google.com/earth-engine/datasets/catalog/GOOGLE_CLOUD_SCORE_PLUS_V1_S2_HARMONIZED.

309 **Acknowledgments**

310 We thank the Google team to not only provide the Google Earth Engine but also the
 311 CloudScore+ cloud product, which greatly facilitated our work.

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