MethaneScan® Technical Brief

Estimation Methods

A Note on Peer-Review Standards

We are constantly incorporating new data and peer-reviewed practices while we drive the development of state-of-the-art estimation, attribution, and uncertainty quantification methods, setting the highest industry standard for accurate, precise, and transparent reporting via direct satellite observation. Superscript references contained within this document (and listed and linked at the end of this brief) show how MethaneScan® draws upon the peer reviewed literature and methods established in that literature. Features specific to MethaneScan® that are either proprietary or still awaiting review (i.e., techniques to be published by our research team) are identified with an asterisk (*). Figure 1 also outlines where we use open-source data to derive data products with methods founded in techniques and results from peer-reviewed literature.

Overview

We estimate company-level oil and gas (O&G) emission intensities (i.e. standardized emission volume/production volume) using two data products we derive from open-source satellite data and atmospheric models, including:

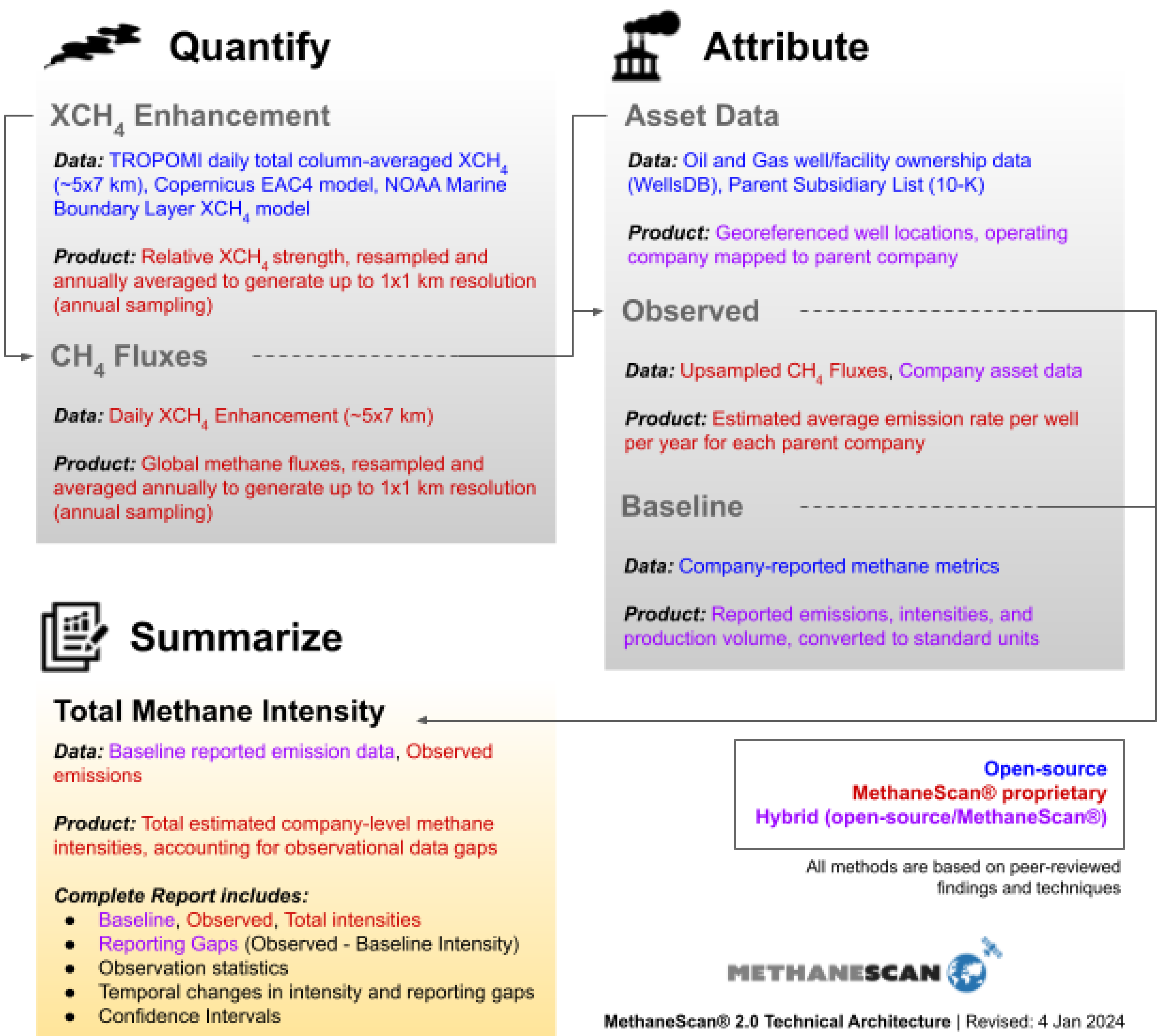
1. Global enhanced methane concentrations
2. Global methane fluxes, derived from (1)

The full MethaneScan® 2.0 technical architecture is depicted in Figure 1. The primary input data source for these products is the TROPOMI sensor[1] on board the Sentinel-5P satellite, which measures daily atmospheric methane concentrations at a raw nadir resolution of 5x7 km^2. These data have been extensively validated using independent methane observations from spaceborne and ground sources[1-4].

Global methane concentrations vary temporally (seasonal variations) and spatially (at local and regional scales) due to factors such as latitudinal trends, naturally-occuring CH_4 emissions (e.g. wetland flooding), or in the case of satellite observations, ground surface elevation. We account for potential biases from these variations by normalizing the observed methane concentrations to derive their enhancements relative to the background concentration at various spatial scales. First we consider global backgrounds to account for non-emission variations* (Product #1: *XCH_4 Enhancement*), then derive local backgrounds[5-6] in order to estimate daily methane fluxes[5] (Product #2: *CH_4 Fluxes*), allowing us to account for the build-up and transport of recent emissions. Refer to Figure 1.

Figure 1

MethaneScan® 2.0 Technical Architecture to Derive Company-Level Total Methane Intensities



Despite having global daily sampling, cloud cover and other data quality concerns (noise and inconclusive retrievals) lead to spatial and temporal gaps in TROPOMI coverage over any given wellhead or company asset on a given day. For Products #1-2, we improve both the spatial coverage and resolution by resampling the ~5x7 km^2 data to a uniform 1x1 km^2 grid and increasing the temporal window over which the observations are averaged[7] (annual mean, sampled annually). As the number of observations over a given area increases, so too does the spatial coverage, our confidence[8] in the observed methane concentrations/fluxes, and the resolution[7], which will vary between the original resolution (one observation) and the size of a grid cell (many observations from varying imaging geometries). An increase in spatial resolution is especially important for the accuracy of emission-attribution to a given well and, subsequently, its owner.

Though we are able to achieve up to 1x1 km^2 resolution with TROPOMI data, there are still often multiple wells within an area of this size, leading to uncertainty regarding pinpoint attribution. However, the goal of MethaneScan® is to standardize and report emission intensities at the **company level** (*not* at the well level) by aggregating daily satellite observations using statistical analyses. In short, a high number of observations per well leads to finer resolution and/or higher confidence in estimated emission rates, and a larger proportion of observed company assets across many geographic regions in which it operates leads to a greater confidence[8] in the company's total score/intensity. We provide further details supporting this generally-accepted statistical concept below.

Another source of attribution uncertainty is non-O&G emitters. The two major point sources of methane in the United States after oil and gas are coal mines and landfills. All oil and gas facilities that are geographically co-located with these point sources (i.e., within a 5 km radius of a coal mine or within a 2 km radius of a landfill facility) are excluded from our dataset.

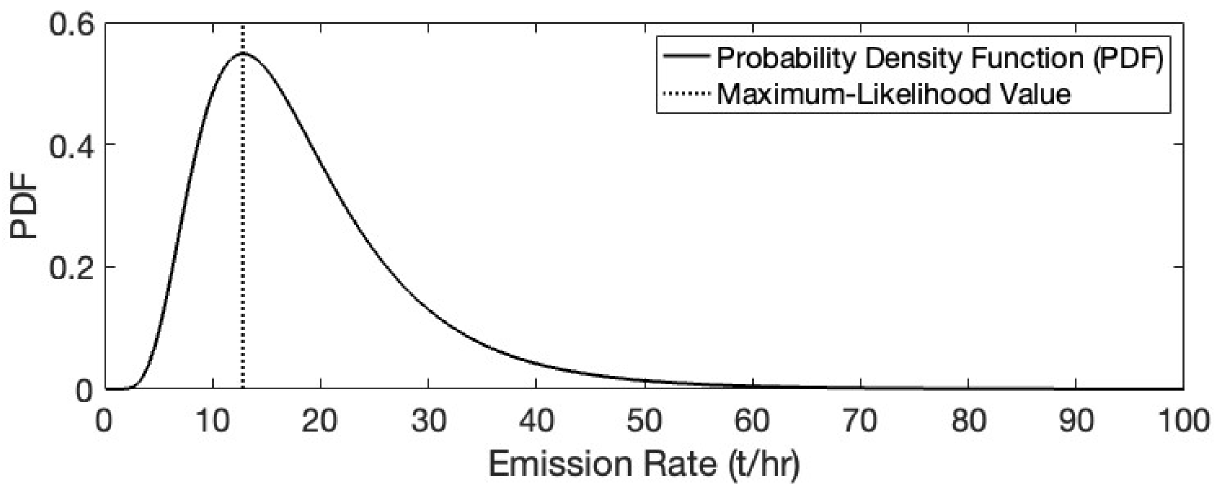
A Note on Resolution

The primary satellite data that we use (TROPOMI) provides global coverage at a native nadir resolution of 5x7 km^2. Though the satellite observes the entire globe daily, clouds or other quality concerns can lead to temporal data gaps. Despite these gaps, a 1x1 km^2 grid cell (pixel) in the US typically has an observation frequency in the range of daily to weekly. We leverage this high sampling frequency to improve the spatial resolution of temporally-averaged observations[7] from ~5x7 km^2 to up to 1x1 km^2, where the exact resolution depends on the number of samples available (more samples lead to better resolution) and the exact native ground footprints. For complete transparency, we distinguish between a pixel and a resolution element (RE), the latter of which is a geographic footprint whose measurement is strictly independent of the surrounding observations. Regardless of post-averaging RE size, we subsample the observations to a 1x1 km^2 grid, but note that the RE is usually approximately equal to the 1x1 km^2 pixel.

Sources of Uncertainty

There are two primary categories of uncertainty related to company-level scoring: quantification and attribution. Quantification uncertainty is subject to the precision and accuracy with which we derive observation values (methane concentration, fluxes, and emissions). On the other hand, numerous methane sources and/or companies operating within a single RE lead to uncertainty in attributing an observed value to a particular company. We account for these uncertainties with probability distributions related to each category and statistical sampling methods. For example, Figure 2 demonstrates that an emission estimate may be represented by a lognormal distribution* (positive values only), the width and location of which we define based on detection sensitivity thresholds, the precision of satellite measurements used as input data, and the method we use to derive the emission rate. When computing company scores, we use Monte Carlo[8-9] (MC) methods to sample an emission rate from its distribution thousands of times, then proceed to attribution sampling.

Figure 2
An emission estimate is defined by its probability density function (PDF)



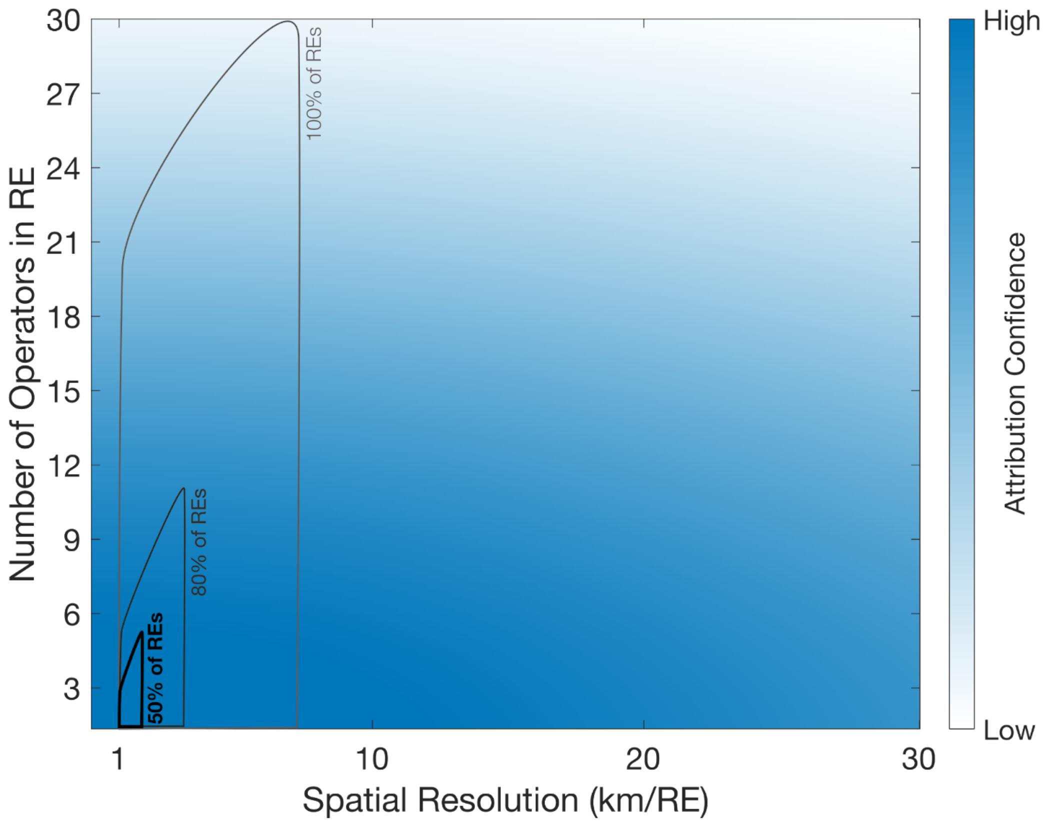
Resolution and Attribution Uncertainty

A given observation can only be attributed to an individual asset in the limiting case that it is the sole potential methane source within the RE. However, our data product is primarily designed for attribution of methane intensities to a company, not an individual well. Therefore, our attribution uncertainty depends not on the number of wells in a RE, but on the proportion of wells belonging to different operating companies and the overlap with other methane sources such as coal mines. Figure 3 conceptually demonstrates that the confidence in attribution to a single company will decrease with increasing number of operators in a RE (y-axis). Likewise, confidence will decrease as the RE increases in size (x-axis) due to a possible increased overlap with other methane sources. To summarize, we have the highest attribution confidence when both the RE size and number of operators are smallest (1 km and 1 operator, respectively).

The contours in Figure 3 demonstrate a typical well density in the context of these two factors, where the majority of REs for resampled methane concentrations and fluxes (Products #1-2) have high spatial resolution (~1x1 km^2) and a small number of operators. The vast majority of wells fall within a fine resolution element (approaching 1x1 km^2) and a small number of different operators. In a 12-month survey ending September 30, 2022 of the top 25 US producers*, we found that:

- Over half (54%) of active wells had 3 or less unique operators in a 1x1 km^2 pixel
- One third had 2 or less unique operators
- 13% had just one operator

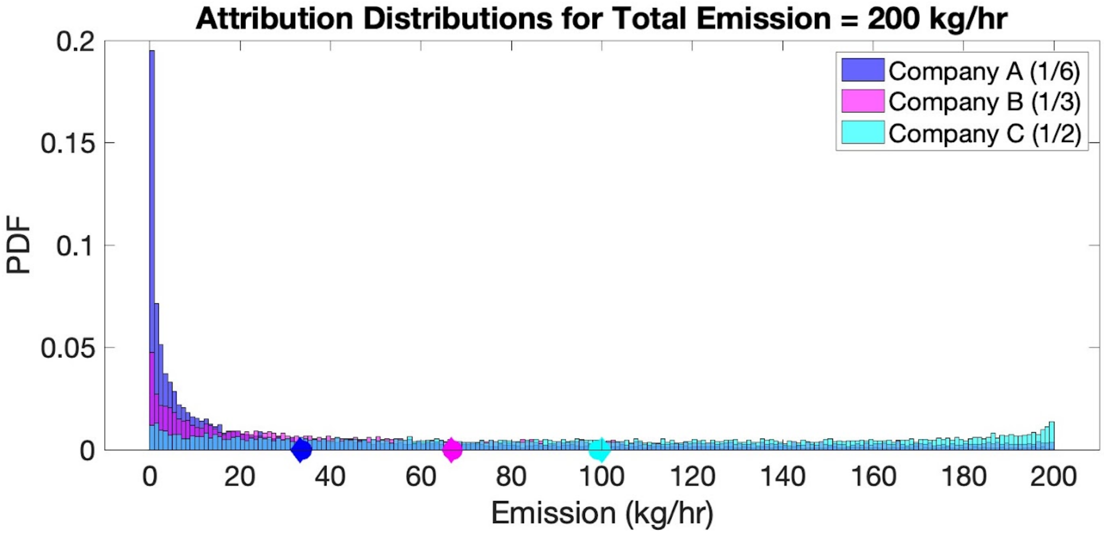
Figure 3
Attribution Confidence by Operator Density



Regardless of RE size, we represent the attribution uncertainty of a given observation with empirically-derived probability density functions based on the proportion of assets belonging to companies operating within the RE. The probability density functions for attribution will resemble truncated distributions* ranging between 0 t/hr and the observed emission rate, with a shape depending on the company's proportion of wells in the RE. An example is shown in Figure 4, in which Companies A, B, and C have 1/6, 1/3, and 1/2 of potential methane sources in the pixel, respectively. These empirical PDFs are the result of MC[8-9] sampling. The averages (large circles) are equivalent to the companies' proportion of sources, relative to the total emission rate (200 kg/hr in this example). Via our sampling methods, the quantification and attribution uncertainties propagate to the company-level emissions/scores.

Figure 4

Probability Density Functions (PDF) for Attributing a Given Emission to Companies within an Observation Pixel

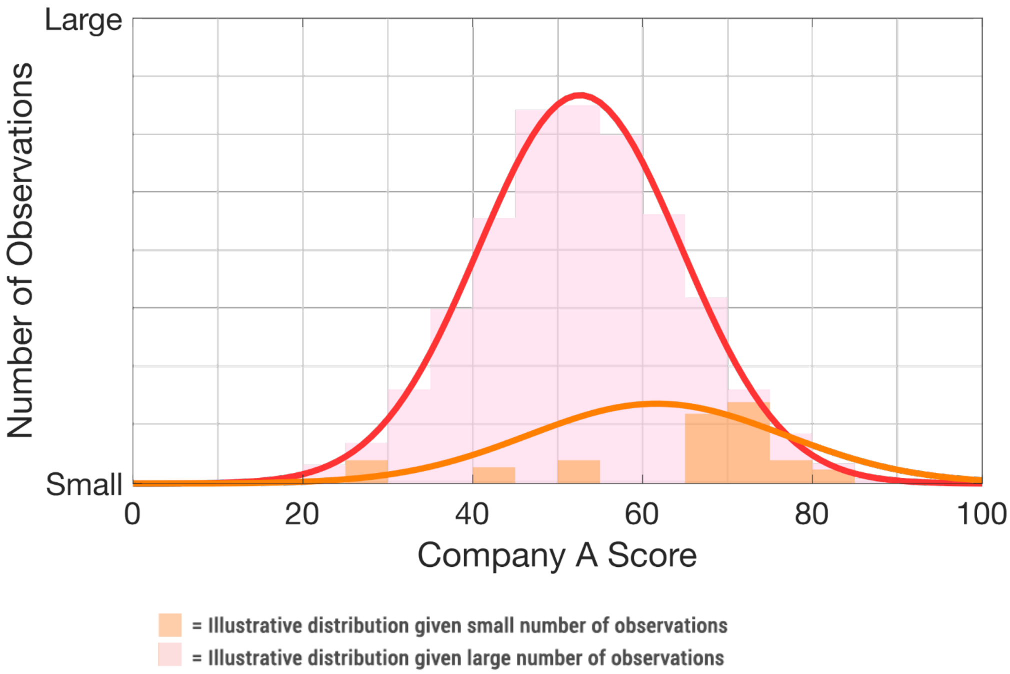


Confidence in Company-Level Scores

Figure 3 highlights that there is attribution uncertainty in most observations; likewise, there is inherent uncertainty in the quantification of concentrations, fluxes, and plumes. However, we do not derive company scores based solely on one sample – even if we had pinpoint resolution – because most mid-to-large producers operate in multiple pixels, sometimes in hundreds to thousands of them. The same operating companies are rarely consistently adjacent to one another or systematically associated with another observation bias. Therefore, the overall company performance and uncertainty can be gleaned by statistically aggregating the observations across all available company samples into a final distribution of potential emissions. In essence, we are leveraging the principles of the Law of Large Numbers[10] (LLN) in the context of MC[8-9] methods. The LLN states that as the number of samples increases, the average of the samples approaches the true expected value (i.e., expectation) of the distribution. We first use this to derive a company's expected methane intensity by leveraging all of its observations in space and time within a given temporal window. Consider, for example, sample Company A in Figure 5. With few observations (orange) the distribution may be biased by the scores of other companies operating in close proximity and it is not clear how the company is performing as a whole due to the wide and flat curve. As the number of samples increases (pink), the distribution narrows to reveal a strong confidence in the mean of Company A's scores. In other words, the distinct "signature" of a company's operation at many sites makes it distinctive from the operations of another company. We refine a company's emissions distribution and quantify the uncertainty with MC methods, in which we generate a set of company-level emission values by randomly drawing the emission quantity and attribution from the respective PDFs. Millions of these samples reveal company-level methane intensity distributions that account for quantification and attribution uncertainty.

Figure 5

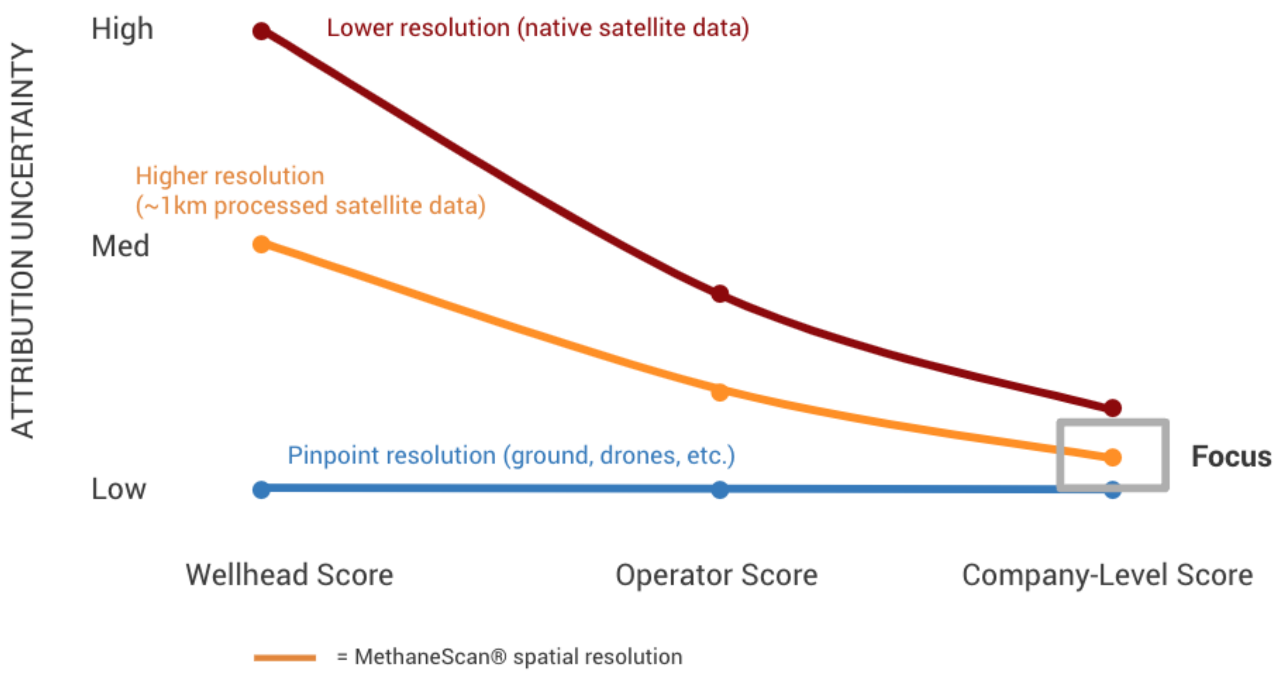
The "Signature" of a Given Company's Methane Score is Revealed When There are a Large Number of Observations Across Many Sites



Combining the theories described above, the attribution uncertainty for our methodology* is summarized in Figure 6. At 1-7 km resolution, the attribution uncertainty for a given wellhead is non-zero. However, an individual wellhead is only one single element of a much larger whole (akin to a single brush stroke in Seurat's pointillist masterpiece *Un Dimanche Après-Midi à L'Île de la Grande Jatte*). When we expand our attribution to the company level (the focus of our products), the uncertainty decreases substantially. Likewise, the greater image of methane intensities across all companies comes into clearer focus.

Figure 6

Attribution Uncertainty is Low for Company-Level Scores at 1 km Resolution



The value of comparable, relatively low-cost observations over many facilities, operators and geographies via satellite does not preclude the value of localized measurements. In fact, local observations are essential for pinpointing the location of specific leaks and, in some cases, monitoring the effectiveness of efforts to plug methane leaks. The utility of one scale, however, does not negate the utility of observations at another scale. Which scale is appropriate depends on the inference that one seeks. Our observations focus on the comparability of corporations, on behaviors and patterns that rise above individual sites and the precise locality of an individual methane leak.

In summary, direct satellite measurement – at up to 1km resolution – represents the best available technology for **company-level** reporting of emission intensities as well as targeting of aircraft/drones/ground sensors when and where higher resolution is needed for pinpoint attribution of a specific facility or leak. Observations made at a pilot level via aircraft/drones/ground sensors typically generate only a few samples in relatively limited geographic areas (i.e., they may not be representative of company-level emissions) whereas satellites provide more frequent observations at a much larger scale – and at much lower cost.

Confidence Metrics by Company

MethaneScan® scores are updated on an annual basis. Each annual update includes confidence metrics for every company in the coverage universe (currently the top 100 listed global producers by market capitalization). Confidence metrics are calculated based on total-observation Monte Carlo sampling from quantification and attribution probability density functions.

Why Are Gaps Between Reported and Observed Emissions So Large?

Users of MethaneScan® data will note some large gaps between a company's reported and observed methane intensities. This disparity has been well-documented and confirmed with airborne studies[11-16]. The cause has been attributed to a number of factors, including the lack of reporting regulations, widespread use of outdated "bottoms-up" approaches to emission estimation (i.e., the application of published emission factors to the total amount of purchased fuel consumed by a particular source), and findings that the top 5% of sources contribute over 50% of emissions and often occur during abnormal operating conditions that are likely to be missed by standard inventory procedure[11]. As reporting regulations are implemented (e.g. OGMP 2.0 Framework[17]) and direct methane measurements become standard practice – as required by the 2022 Inflation Reduction Act beginning January 2024 – we expect the gap between reported and observed intensities to narrow.

References & Peer Review

The following published papers directly inform the implementation of MethaneScan®. These papers are published in the remote sensing and atmospheric science literature, having been peer reviewed during the publication process. The papers form the basis of interpreting data from the TROPOMI sensor, ways of addressing bias and other factors that affect signal quality over space and time, considerations of resolution and attribution to methane sources on the ground, and the degree to which satellites are detecting methane that appears to be underestimated from other ground-based sensors. This literature is rapidly growing and evolving, with this reference list being regularly augmented and updated with published studies that are incorporated in or inform MethaneScan® analytics.

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