SATELLITE REMOTE SENSING - A NEW TOOL FOR EMISSIONS MANAGEMENT –REVIEW OF APPLICABLE TECHNOLOGIES

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Abstract

This paper summarises the first stage of an ACARP Research and Development project to evaluate the utility of satellite remote sensing for air quality management within the mining industry. The project investigates the options available using both publicly available and commercial data sets generated by the latest generation of satellite imagery.

The two metrics that are routinely observed using satellite imagery relevant to the mining industry emissions are methane (XCH4) and particulate matter (Aerosol Optical Depth; AOD). The former is relevant for greenhouse gas management, the latter for mine-site dust management.

In addition to identifying the benefits of currently available technology and techniques, this work will also critically evaluate the limitations and constraints of the technology.

In the case of methane observations, use of ‘top-down’ (satellite) based estimates can challenge / validate the ‘bottom up’ (empirical observations) values that are currently being used for emission estimation under the National Greenhouse and Energy Reporting (NGER) scheme. Any refinement to methane quantification (from exposed coal, overburden and interburden) will lead to refinement of financial obligations under any future price on carbon.

In the case of regional particulate transport, even a qualitative evaluation of a specific dust event, viewed at a regional scale, can assist with understanding, and ultimately managing, dust emissions.

The approach to this study involves the completion of an extensive literature review of the state-of-the-science as it relates to high spatial and temporal observations of methane and particulate matter using satellites. Dependent upon the outcomes of this research, one or both of these remote sensing techniques may be taken forward for a ‘deep dive’ into its applicability for mining emissions management. The current paper provides a summary of the outcomes of this first stage of the project.

Keywords: Satellites, Methane, Particulate, TROPOMI, ACARP, Himawari

1. Introduction

The objective of this work is to review the value of current, future, and proposed satellite observations to better quantify and understand methane and PM emissions associated with the mining industry.

We provide an extensive literature review of the state-of-the-science as it relates to high spatial and temporal observations of methane and particulate matter using satellites. Dependent upon the outcomes of this research, one or both of these remote sensing techniques may be taken forward for a ‘deep dive’ into its applicability for mining emissions management.

During our evaluations, we identify what can, and cannot, be achieved using existing satellite information. We document the limitations and areas of uncertainty within the technology / techniques.

2. Methane remote sensing

2.1. Instrumentation

Multiple methane-detecting satellites are either in place or planned for launch over the next two to three years. Each satellite / group of satellites has distinct capabilities and purpose, and their funding ranges from public sector, private sector and non-profit.

The methane-detecting satellites that are currently deployed can be divided broadly into:

- Area Flux Mappers: can track methane over very wide areas but can see only large emissions and lack the resolution to identify individual sources;
- Point-Source Imagers: have fine-grained spatial resolution for targeting known sites but lack sensitivity to detect smaller emission sources.

The next generation of methane-detecting satellites, such as MethaneSAT, are designed with the capability to bridge the gap: with a wide field of view to detect methane sources across wide areas with high precision.

The TROPOMI instrument was launched in 2017 on board the Sentinel-5 Precursor (Sentinel-5P) satellite, a Low Earth Orbiter (LEO) with a sun-synchronous orbit that overpasses at 13:30 local solar time. Daily global coverage offered by TROPOMI is a useful way to spot high emission events, and can be used as a tool to look for possible targets for other point-source orientated satellites.

A different observing strategy by the privately-operated GHGSat (first instrument launched in June 2016) targets limited viewing domains with very fine pixel resolution to detect a wide range of methane point sources.

It is envisaged that in the future, full constellations of imagers, covering the globe daily, will become available. At present, intermittent high-resolution imagery can be coupled with regular low-resolution images (such as from TROPOMI) to fill the gaps in coverage.

Capability for regional mapping of methane emissions is expected to greatly expand in the future with the MethaneSAT, GOSAT-GW, and CO2M instruments. (Jacob et al, 2022).

Targeted observation of methane point sources from space began with the 2015 Aliso Canyon blowout using the Hyperion hyperspectral sensor (Jacob et al., 2022). Hyperspectral and multispectral imaging spectrometers designed to observe land surfaces at high spatial resolution (Hyperion, PRISMA, Sentinel-2, Landsat-8/9, WorldView-3) have also shown capability to detect large methane point sources in their short-wave infrared (SWIR) bands.

For example, Varon et al., 2021 have demonstrated the capability of the current Sentinel-2 twin satellites to detect and quantify strong methane point sources globally with both fine pixel resolution and frequent revisits. Sentinel-2 was originally designed to provide operational data products for environmental risk management, land cover classification, land change detection, and terrestrial mapping, as a complement to the Landsat and SPOT satellite missions. Sentinel-2 comprises two satellites positioned 180° out of phase in the same sun-synchronous orbit, with an Equator-crossing time of 10:30 (local solar time) at the descending node. Sentinel-2A was launched in 2015 and Sentinel-2B in 2017. Each satellite carries a MultiSpectral Instrument (MSI) that continuously sweeps the Earth's surface in 13 spectral bands from the visible to the SWIR at 10–60m pixel resolution over a 290 km cross-track swath. The twin satellite configuration enables full global coverage every 5 day and 2–3 day revisit rates at midlatitudes. Varon et al. (2021) demonstrate that Sentinel-2 SWIR bands 11 (~1560–1660 nm) and 12 (~2090–2290 nm), with 20 m pixel resolution, can be used to detect methane plumes from point sources and quantify source rates.

Figure 1 shows the classification of satellite instruments by their capability to observe atmospheric methane on global scales, on regional scales with high resolution, and for point sources.

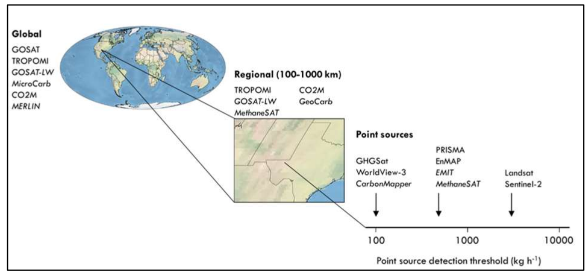


Figure 1. Satellite instruments classified according to ability to observe Global, Regional and Point Source Scales (Jacob et al, 2022)

2.2. Methods

Atmospheric methane is detectable by its absorption of radiation in the SWIR at 1.65 and 2.3 µm, and in the thermal infrared (TIR) around 8 µm. Satellites equipped with SWIR instruments measure solar radiation backscattered by the Earth and its atmosphere (Jacob et al, 2016).

The general principle used for methane quantification is similar across the majority of satellite sensors, a schematic of which is shown in Figure 2.

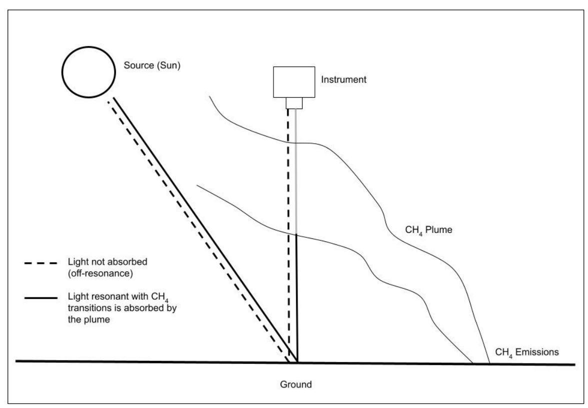


Figure 2. Schematic showing the spectrally specific absorption of reflected sunlight (earthshine) by a CH4 plume and detection by satellite (after Day et al, 2017)

Figure 3 shows the shows the atmospheric optical depths of different gases in the SWIR, highlighting the methane absorption bands at 1650 and 2300 nm. All first-generation solar backscatter instruments operated at 1650 nm, however TROPOMI operates at 2300 nm. GOSAT-2 operates at both (Jacob et al., 2016).

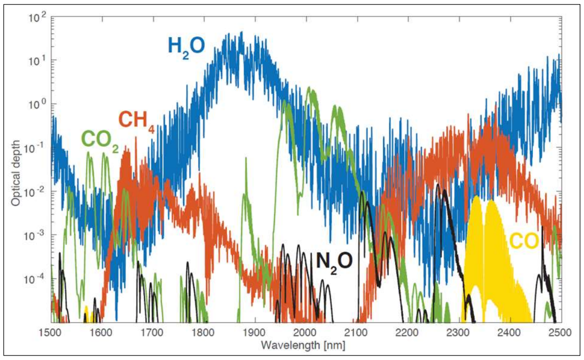


Figure 3. Atmospheric optical depths of major trace gases in the SWIR (Jacob et al, 2016)

2.2.1. Data retrieval and screening

The majority of recent peer reviewed papers using methane-detecting satellites have been completed using the TROPOMI data set. As such, additional detail in the methods of accessing, processing and interpreting these data is provided.

Current TROPOMI CH_4 observations, which are available for the inner two-thirds of its total swath and only over land, are vertically integrated columns sensitive to the troposphere. With an effective swath of ~1750 km wide from the along-track position and a ground pixel size of 7 km x 5.5 km, TROPOMI CH_4 data can provide near-global daily coverage at high horizontal resolution over land, but they are limited by cloud cover and retrieval quality (Barre et al., 2021).

The European Space Agency (ESA) releases both Level 1 and Level 2 data products. The Level 1 data product represents raw radiance and irradiance measurements from the TROPOMI instrument.

TROPOMI methane retrieval is generally completed using the TROPOMI operational CH_4 data product (Hu, 2016), which implements the RemoTec retrieval algorithm. The operational algorithm uses a two-band retrieval approach using the NIR and SWIR bands. The SWIR band contains the CH_4 information and the NIR band is used for correction for aerosols.

Level 2 data products are released in terms of XCH4, the column-averaged dry air mixing ratio for methane. This is expressed as a concentration (ppb) within the column of air being observed by the satellite at a given point in time during its orbit. Values of XCH4 include the scientific and operational XCH4 data products (used by Sadavarte et al., 2021a) and the XCH4 bias corrected data product (adopted by Lauvaux et al., 2022).

2.2.2. Plume detection

Lauvaux et al. (2022) describe the approach taken by their automated plume detection algorithm, with plume enhancements defined as >25 ppb averaged over several pixels.

At every orbit, the TROPOMI instrument produces 13 to 14 images (tiles) with a 2600 km swath width. Each tile is then processed with a plume detection procedure. The mean, median and standard deviation of a given pixel is calculated by comparing an 11 × 11 pixel ‘patch’ with the pixel of interest at its centre. These data are then used to create an ‘anomaly map’ across the whole image. Adjacent, overlapping plumes are then separated using a technique known as watershed separation. Initial plume identification (by tracing any identified plumes upwind) is then confirmed by human labelling. A visualisation of this process is provided in Figure 4.

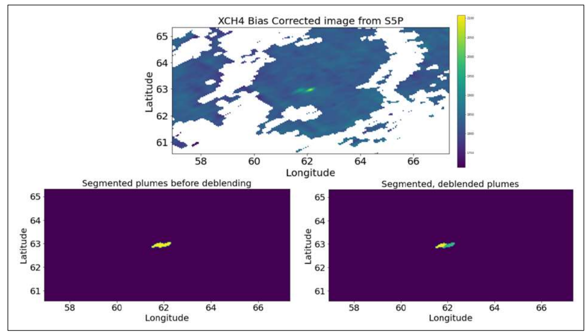


Figure 4. Major steps in plume detection algorithm, including deblending step (Lauvaux et al. 2022)

The final step employed in plume detection is human labelling. This involves rejection of candidate plumes according to the following criteria (Lauvaux et al., 2022):

1. Plume is inconsistent with the wind direction from the ERA5 reanalysis product (i.e. plume formation is inconsistent with the prevailing wind direction at the time);
2. Plume spatial distribution correlates with that of the Surface Albedo SWIR product provided by Sentinel-5P (i.e. plumes with strong correlation to surface albedo are rejected);
3. Plume spatial distribution correlates with spatial patterns visible in optical images (for the same rationale as above).

2.2.3. Inferring methane emissions

The studies within the literature generally seek to use values of XCH4 within identified plumes to then quantify the individual methane emission sources that have led to these enhanced concentrations being observed.

A number of techniques have been used to quantify the mass emission of methane, Q (Schneising et al, 2020). All of these techniques require the derivation of mass emission using satellite-observed total column methane (in ppb) and referencing concurrent meteorology to estimate methane flux (so-called inverse methods).

Jacob et al., 2022 summarises seven different methods for inferring source rate, Q, from satellite observations of instantaneous plumes of methane column enhancements ΔΩ [kg m-2] relative to background.

A graphical summary of these methods is provided in Figure 5.

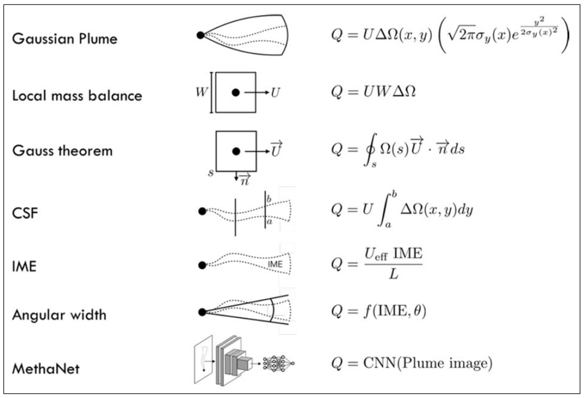


Figure 5. Seven methods to estimate point source rates Q from satellite-observed methane column enhancements (Source: Jacob et al, 2022)

2.3. Limitations and uncertainties

2.3.1. Temporal / spatial limitations

An issue with all LEO satellite data is that, by definition, they only provide a snap-shot in time, for the period when the satellite is above the area of interest. In the case of the TROPOMI instrument, this is one observation daily.

The GHGSat-D, however, has an average revisit time of about two weeks, depending on latitude.

Jacob et al. (2022) note that observing point sources from space has unique requirements; plumes are typically less than 1 km in size, thus requiring satellite pixels finer than 60 m.

2.3.2. Interference from clouds, humidity and aerosol

Methane-detecting satellites require the area of observation to be cloud-free. In the work completed by Sadavarte et al, 2021, a total of 124 clear-sky observations (over 75 orbits) passed the data screening process, over a full two years of potential observations.

On average in 2019, the TROPOMI sensor successfully retrieved a XCH4 measure for 7% of daily onshore pixels. The distribution of missing pixels is not homogeneous however, as some places (e.g. equatorial zones) are essentially missing whereas drier places have more than 100 measures per year. Considering only onshore pixels with at least 10 valid XCH4 measures in 2019, the daily proportion of covered pixels increases to 13% (Lauvaux et al, 2022). This is illustrated in Figure 6.

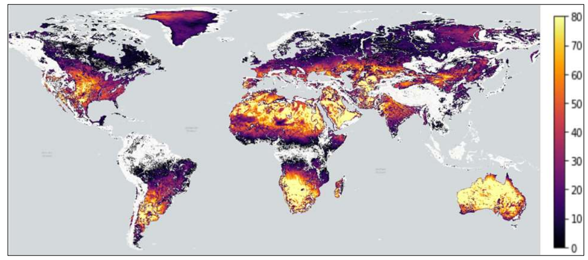


Figure 6. Number of days TROPOMI provided at least one (quality filtered) XCH4 measurement during 2019 (Source: Lauvaux et al., 2022)

Measurements in the SWIR spectral region from 2000 to 2500 nm sample absorption features from water vapor, carbon dioxide, and methane (refer Figure 3). The 2100 to 2450 nm window is especially sensitive to methane and for this reason this wavelength band was adopted for methane retrievals by Irakulis-Loitxate et al. (2021).

2.3.3. Instrument noise / artifacts

CSIRO referenced GHGSat satellite imagery from late 2016 (Ong et al., 2017), and note that these were some of the first data acquired by GHGSat. Consequently, the data experienced some of the post launch issues related to the new sensors.

CSIRO concluded that there remains important uncertainties associated with the quantitative use of the methane concentration map as delivered from GHGSat. Specifically, the level of instrument noise / artefacts remained a concern and there appeared to be influences of the local geology, landforms and/or compositional material that may require to be accounted for in the retrieval of the methane products (Ong et al., 2017b). They note that the methane concentration image can potentially be improved visually with noise removal techniques. While the application of such techniques improve the visual look of the methane concentration map, CSIRO concluded that it will not improve the accuracy of the data.

CSIRO's conclusion (Ong et al., 2017) is applicable to other methane remote sensing solutions apart from GHGSat. Namely, that the measurement of methane from space is a highly demanding task because the sources are usually small, compounded by the large vertical column from space to earth (>500 km). Further, the spectral features are very narrow and the spectral region where these features occur overlap with other atmospheric features (water vapour) and other surface features (minerals and dry plants). In addition, passive sensors rely on sunlight to provide the illumination/energy, which is generally quite low in those spectral regions. The signal received from fine-pixel instrumentation would also be small because it is integrating over a small area. This is opposed to other GHG sensors which are integrating over much larger areas to obtain higher signals.

Finally, Varon et al. (2020) note that satellite scenes can illustrate GHGSat-D retrieval artefacts resulting primarily from striping noise, surface reflectance variability, and stray light. Some artefacts were found to be similar in magnitude to the plumes, which led the authors to highlight the importance of prior knowledge of source location.

2.3.4. Spatially variable bias

Surface albedo bias occurs in methane-detecting satellite data. This is screened by rejecting orbits that show a high correlation of XCH4 with surface albedo.

Biases induced by the albedo in the XCH4 retrievals from TROPOMI (and other satellite instrumentation) are well-known but not properly removed in the official Level 2 data product (ESA 2020). To overcome this, it is good practice to discard all detected plumes with a strong correlation with the surface albedo to avoid false positives. For the same reason, all plume candidates matching spatial patterns visible in optical images should be removed from analysis.

2.3.5. Use of ERA5 meteorological data set

The ERA5 global meteorology is often referenced in inferring methane emissions. These data are coarse, at a resolution of approximately 30 km × 30 km. Application of wind speeds derived at this resolution introduces significant uncertainty in the source rate.

Jacob et al. (2022) note that lack of precise wind speed information is a major source of error for interpreting satellite observations because plume concentrations vary as the ratio Q/U, meaning that errors in U propagate linearly to errors in Q.

Varon et al. (2018) highlight that while low winds are beneficial for source detection, they are detrimental for source quantification. This is problematic for source quantification in, say, the Bowen basin of Queensland, where average wind speeds are low given the semi-tropical location. Varon et al. (2018) conclude that additional error applies if local wind speed measurements are not available and may dominate the overall error at low wind speeds.

2.3.6. Reliance upon bottom-up inventory data

Bottom-up emission inventory data is used in satellite methane emission estimation, both for comparison against satellite-derived emission estimates, and to subtract other sources that may be seen in methane plume observations from a given source. Both the spatial and emissions granularity of the bottom-up inventory data present issues.

Sadavarte et al. (2021) state that the estimated contributions from other surrounding anthropogenic sources (coal mines, coal seam gas (CSG) activities, etc) are subtracted from downwind plume prior to the final calculation of source rate Q.

Other anthropogenic sources are estimated using bottom-up emission estimates in the public domain. This is problematic, since much of this information relied upon the global GHG emissions dataset EDGARv4.3.2, which was published in 2017 and represents the most recent year 2012 (JRC, 2022). EDGARv4.3.2 was relied upon to provide estimates for coal mine activity, with 2012 values subsequently scaled proportionally relative to changes in coal production for Queensland between 2012 and the analysis years (2018-19). It was also relied upon to derive estimates for other sources in the database, including energy, transport, wastewater, landfills, agriculture including livestock, paddy cultivation. Estimation of Oil & Gas methane generation referenced the global methane inventory by Scarpelli et al. (2020) available for the calendar year 2016. All inventory sources are provided on a 0.1° × 0.1° grid resolution (approximately 10 km × 10 km). This means that multiple sources may be aggregated within a single grid square, with significant opportunity for sources to be confounded at such spatial resolution.

Connecting top-down information on methane emissions to the improvement of bottom-up emission inventories remains a challenge (Jacob et al., 2022). Ultimately, the goal of top-down estimates must be to improve bottom-up inventories, as the latter provide the foundational tools for climate policy by relating emissions to processes. Where discrepancies are identified by satellite for a particular sector, this should motivate work to improve activity and/or emission factor estimates for that sector. The new International Methane Emissions Observatory (IMEO) aims to facilitate this infusion of top-down information into the improvement of bottom-up inventories

3. Particulate Matter

Using satellite data to estimate ground-level particulate matter (PM) concentrations still remains difficult. There are two main methods in the literature, one using the differences in brightness temperature (BTD) (Sowden et al, 2020), using the infrared wavelengths, and the other focussing on aerosol optical depth in the visible spectrum.

Aerosol Optical Depth (AOD) is a measure of the extinction of electromagnetic radiation by dust and haze, which can absorb or scatter light. It is dimensionless and is related to the total amount of aerosol in the vertical column of the atmosphere over a specific location. It expresses the quantity of light removed from a beam of light by scattering and/or absorption during its path through the atmosphere. It can be measured both from space (via satellite) and the ground (via the AERONET network).

The methodologies using AOD to estimate PM have been well researched in peer-reviewed papers for the last 20 years (Li et al., 2015, Zaman et al., 2017, Sotoudeheian et al., 2016, Yumimoto et al, 2016). Much of this work has been done using retrievals from the MODerate-resolution Imaging Spectro-radiometer (MODIS) instrument on NASA's Terra satellites. Measurements from these LEO satellites are temporally limited but have superior spatial resolution to the newer generation of Geostationary Earth Orbit (GEO) satellites such as Himawari-8.

The Himawari AOD retrievals have been shown to have good correlation with ground based AOD measurements from the AERONET network (She et al, 2018, Zhang et al. 2018) as shown in Figure 6.

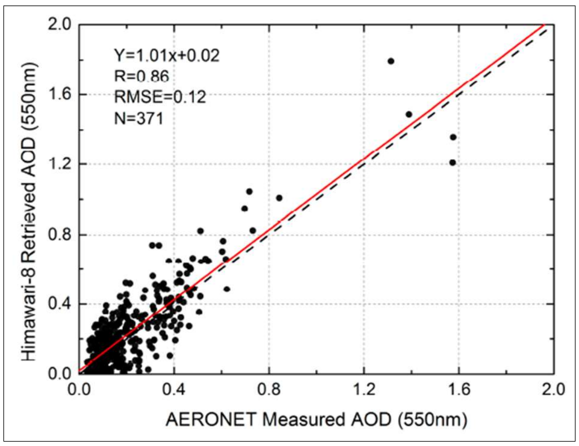
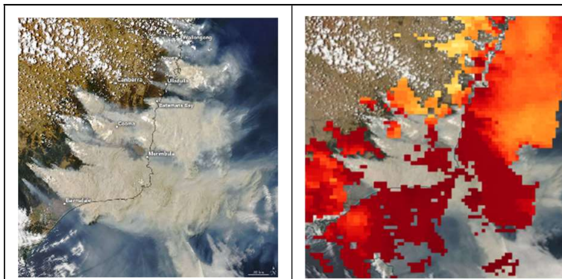


Figure 6. Scatter plots of Himawari AOD against AERONET AOD (Source: Zhang et al., 2018)

Statistical models developed to estimate PM from AOD have shown that direct comparisons are poor and that non-linear multivariant regression models improve these estimates as they take into account meteorological parameters and, in some instances, landuse (Ghotbi et al., 2016). There is still work required to improve these algorithms as there can be significant gaps in datasets, confounding the PM-AOD relationship. An example of this can be seen by comparing two images from the MODIS instrument on the same day – January 4, 2020, during the bushfires on the east coast of Australia (Figure 7). The AOD shows considerable data gaps over some of the most intense areas of high PM.

As AOD is, by definition, limited to the visible spectrum, the temporal resolution will always be low (i.e. daytime only). Work done to compare AOD with ground-based measurements is therefore limited to longer timeframes and the conflict with continuous data requirements for air quality applications remains. The main advantage of using the alternative BTD methods is that it uses the infrared spectrum, enabling measurements 24-hours per day and therefore achieving high temporal resolution. This method has had limited success to date (Sowden, 2020b), due to confounding factors such as water vapour / clouds inhibiting the determination of aerosol composition. However, more work is being completed to develop methods to improve it. Development of a successful technique could have significant practical applications for mining areas in the future and should be watched with interest.



Visual image	AOD overlaid on visual image

Figure 7. Comparison of MODIS visual and AOD images on 4 January, 2020
(Source: https://worldview.earthdata.nasa.gov/)

4. Next Steps

Global satellite instrument validation exercises are well established, using either satellite-to-satellite comparisons (e.g. TROPOMI vs GOSAT) or satellite-to-ground observation (e.g. Total Carbon Column Observing Network; TCCON). However, except for the limited success of Day et al, 2017, no methane satellite ground-truthing exercises have been completed that are specific to Australian coal mining activities, or their respective geographies.

It is suggested that future investigations could reference directly-measured methane emissions at source (e.g. ventilation air methane measured by the underground coal mining industry in Australia).

To enable such an exercise, a candidate mine would need to be established for comparison against satellite predictions. This would require access to the continuous methane concentration / volumetric flow data from an Australian underground coal mine with limited fugitive methane sources (all methane reporting to upcast ventilation shafts).

The intention would be to use these accurate, ground-based observations to compare with the inferences of methane emissions able to be derived using data from the TROPOMI instrument.

An alternative direction would be to focus the research on gathering field data to ground-truth claims made using satellite observations in isolation. Several researchers (Cusworth et al., 2018, Jacob et al, 2022) acknowledge that synergy with suborbital (ground-based and airborne) platforms is essential for a multi-tiered observing strategy.

Suborbital observations have a unique role to complement the intrinsic limitations of satellites in terms of spatial resolution, return time, cloud cover, dark surfaces, and nighttime. Surface measurements are typically ten times more sensitive to local emissions than satellite observations (Cusworth et al., 2018, Jacob et al., 2022).

Finally, given that there is potentially a strong relationship between AERONET AOD and Himawari AOD data, a study relating local AERONET to local PM monitoring data (DPE Merriwa) may be of value.

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References

Barré, J., Aben, I., Agustí-Panareda, A., Balsamo, G., Bousserez, N., Dueben, P., Engelen, R., Inness, A., Lorente, A., McNorton, J., Peuch, V.-H., Radnoti, G., and Ribas, R. (2021): Systematic detection of local CH4 anomalies by combining satellite measurements with high-resolution forecasts, Atmos. Chem. Phys., 21, 5117–5136, https://doi.org/10.5194/acp-21-5117-2021

Cusworth, D. H.; Jacob, D. J.; Sheng, J.-X.; Benmergui, J.; Turner, A. J.; Brandman, J.; White, L.; Randles, C. A. (2018). Detecting high-emitting methane sources in oil/gas fields using satellite observations. Atmos. Chem. Phys., 2018, 18, 16885–16896.

Day, S., Ong, C., Marvig, P., White, S. (2017). Regional methane emissions in NSW CSG basins. CSIRO, Australia. https://gisera.csiro.au/wp-content/uploads/2018/03/GHG-4-Interim-Report.pdf

Ghotbi, S., Sotoudeheian, S. and Arhami, M (2016). Estimating urban ground-level PM10 using MODIS 3km AOD product and meteorological parameters from WRF model. Atmospheric Environment, 141:333-346.

Hu, H.; Hasekamp, O.; Butz, A.; Galli, A.; Landgraf, J.; Aan de Brugh, J.; Borsdorff, T.; Scheepmaker, R.; Aben, I. (2016). The operational methane retrieval algorithm for TROPOMI. Atmos. Meas. Tech., 2016, 9, 5423–5440.

Irakulis-Loitxate, L. Guanter, Y.-N. Liu, D. J. Varon, J. D. Maasakkers, Y. Zhang, A. Chulakadabba, S. C. Wofsy, A. K. Thorpe, R. M. Duren, C. Frankenberg, D. R. Lyon, B. Hmiel, D. H. Cusworth, Y. Zhang, K. Segl, J. Gorroño, E. Sánchez-García, M. P. Sulprizio, K. Cao, H. Zhu, J. Liang, X. Li, I. Aben, D. J. Jacob, (2021). Satellite-based survey of extreme methane emissions in the Permian basin. Sci. Adv.7, eabf4507(2021). https://www.science.org/doi/epdf/10.1126/sciadv.abf4507

Jacob, D. J., Turner, A. J., Maasakkers, J. D., Sheng, J., Sun, K., Liu, X., Chance, K., Aben, I., McKeever, J., and Frankenberg, C.: Satellite observations of atmospheric methane and their value for quantifying methane emissions, Atmos. Chem. Phys., 16, 14371–14396, https://doi.org/10.5194/acp-16-14371-2016 , 2016

Jacob, D. J., Varon, D. J., Cusworth D. H., Dennison P. E., Frankenberg C., Gautam R., Guanter L., Kelley J., McKeever J., Ott L. E., Poulter B., Qu Z., Thorpe A. K., Worden J. R. and Duren R. M. (2022). Quantifying methane emissions from the global scale down to point sources using satellite observations of atmospheric methane. Atmospheric Chemistry and Physics. Preprint. Discussion started: 11 April 2022. https://doi.org/10.5194/acp-2022-246

Jongaramrungruang, S., Frankenberg, C., Matheou, G., Thorpe, A., Thompson, D. R., Kuai, L., & Duren, R. (2019): Towards accurate methane point-source quantification from high-resolution 2D plume imagery. Atmos. Meas. Tech., 12, 6667–6681, 2019

Jongaramrungruang, S., G. Matheou, A.K. Thorpe, Z.-C. Zeng, and C. Frankenberg, (2022). MethaNet – An AI-driven approach to quantifying methane point-source emission from high-resolution 2-D plume imagery, Remote Sensing Environ., 269, 112809

Krings, T., K. Gerilowski, M. Buchwitz, M. Reuter, A. Tretner, J. Erzinger, D. Heinze, U. Pflüger, J.P. Burrows, (2021). 1050 Bovensmann, MAMAP – a new spectrometer system for column-averaged methane and carbon dioxide observations from aircraft: retrieval algorithm and first inversions for point source emission rates, Atmos. Meas. Tech., 4, 1735–1758, https://doi.org/10.5194/amt-4-1735-2011, 2011

Lauvaux C., Giron M., Mazzolini A., d'Aspremont R., Duren D., Cusworth D., Shindell P., Ciais T. (2022). Global assessment of oil and gas methane ultra-emitters. Science 375, 557–561 (2022) 4 February 2022

Li J, Carlson BE, Lacis AA (2015) How well do satellite AOD observations represent the spatial and temporal variability of PM2.5 concentration for the United States? Atmos Environ 102:260–273.

Ong, C., Day, S., Halliburton, B.,Marvig, P., White, S. (2017). Regional methane emissions in NSW CSG basins. CSIRO, Australia. Accessed 25 August 2022 at: https://gisera.csiro.au/wp-content/uploads/2018/03/GHG-4-Final-Report.pdf

Pandey, S, Gautam, R, Houweling, S, Denier van der Gon, H, Sadavarte, P, Borsdorff, T, Hasekamp, O, Landgraf, J, Tol, P, van Kempen, T, Hoogeveen, R, van Hees, R, Hamburg, SP, Maasakkers, JD, Aben, I. (2019). Satellite observations reveal extreme methane leakage from a natural gas well blowout. Proceedings of the National Academy of Sciences 116 (52): 26376-26381

Sadavarte, P, Pandey, S, Maasakkers, JD, Lorente, A, Borsdorff, T, Denier van der Gon, H, Houweling, S, Aben, I. (2021a). Methane Emissions from Super-emitting Coal Mines in Australia quantified using TROPOMI Satellite Observations. Environmental Science & Technology 55(24): 16573-16580.

Schneising, O., Buchwitz, M., Reuter, M., Vanselow, S., Bovensmann, H., and Burrows, J. P. (2020): Remote sensing of methane leakage from natural gas and petroleum systems revisited, Atmos. Chem. Phys., 20, 9169–9182, https://doi.org/10.5194/acp-20-9169-2020

She L, Xue Y, Yang X, Guang J, Li Y, Che Y et al (2018) Dust detection and intensity estimation using Himawari-8/AHI observation. Remote Sens 10(4):490.

Sotoudeheian S, Arhami M (2014) Estimating ground-level PM10 using satellite remote sensing and ground-based meteorological measurements over Tehran. J Environ Health Sci Eng 12.

Sowden M, Blake D (2020a) Which dual-band infrared indices are optimum for identifying aerosol compositional change using Himawari-8 data? Atmos Environ 241:117620.

Sowden M, Blake D, Cohen D, Atanacio A, Mueller U (2020b) Development of an infrared pollution index to identify ground-level compositional, particle size, and humidity changes using Himawari-8. Atmos Environ 229:117435

Varon, D. J., Jacob, D. J., McKeever, J., Jervis, D., Durak, B. O. A., Xia, Y., & Huang, Y. (2018): Quantifying methane point sources from fine-scale satellite observations of atmosphericmethane plumes. Atmospheric Measurement Techniques, 11, 5673–5686. https://doi.org/10.5194/amt-11-5673-2018

Varon, D. J., Jervis, D., McKeever, J., Spence, I., Gains, D., and Jacob, D. J. (2021): High-frequency monitoring of anomalous methane point sources with multispectral Sentinel-2 satellite observations, Atmos. Meas. Tech., 14, 2771–2785, https://doi.org/10.5194/amt-14-2771-2021

Yumimoto K, Nagao TM, Kikuchi M, Sekiyama TT, Murakami H, Tanaka TY et al (2016) Aerosol data assimilation using data from Himawari-8, a next-generation geostationary meteorological satellite. Geophys Res Lett 43(11):5886–5894.

Zaman, N, Kanniah, K. and Kaskaoutis, D. (2017) Estimating Particulate Matter using satellite based aerosol optical depth and meteorological variables in Malaysia. Atmospheric Research 193 (2017) 142–162.

Zhang, W., Xu, H. and Zheng, F. (2018) Aerosol Optical Depth Retrieval over East Asia Using Himawari-8/AHI Data. Remote Sens., 10(1), 137.