



## 1 Potential of next-generation imaging spectrometers to detect and quantify 2 methane point sources from space

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13

### 14 Abstract

15 We examine the potential for global detection of methane plumes from individual point sources with the new  
16 generation of spaceborne imaging spectrometers (EnMAP, PRISMA, EMIT, SBG) scheduled for launch in 2019-2025.

17 These instruments are designed to map the Earth's surface with a sampling distance as fine as  $30 \times 30 \text{ m}^2$  but they have  
18 spectral resolution of 7-10 nm in the 2200-2400 nm band that should also allow useful detection of atmospheric  
19 methane. We simulate scenes viewed by EnMAP (10 nm spectral resolution, 180 signal-to-noise ratio) using the  
20 EnMAP End-to-End Simulation Tool with superimposed methane plumes generated by large-eddy simulations. We  
21 retrieve atmospheric methane and surface reflectivity for these scenes using the IMAP-DOAS optimal estimation  
22 algorithm. We find an EnMAP precision of 4-13% for atmospheric methane depending on surface type, allowing  
23 effective single-pass detection of  $100+ \text{ kg h}^{-1}$  methane point sources depending on surface brightness, surface  
24 homogeneity, and wind speed. Successful retrievals over very heterogeneous surfaces such as an urban mosaic require  
25 finer spectral resolution. We simulated the EnMAP capability with actual plume observations over oil/gas fields in  
26 California from the airborne AVIRIS-NG sensor ( $3 \times 3 \text{ m}^2$  pixel resolution, 5 nm spectral resolution, SNR 200-400).

27 We spectrally and spatially downsampled AVIRIS-NG images to match EnMAP instrument specifications and found  
28 that we could successfully detect point sources of  $\sim 100 \text{ kg h}^{-1}$  over bright surfaces. Estimated emission rates inferred  
29 with a generic Integrated Mass Enhancement (IME) method agreed within a factor of 2 between EnMAP and AVIRIS-  
30 NG. Better agreement may be achieved with a more customized IME method. Our results suggest that imaging



31 spectrometers in space could play a transformative role in the future for quantifying methane emissions from point  
32 sources on a global scale.

33

34 **1 Introduction**

35 Methane is a powerful greenhouse gas, yet its sources are highly uncertain. Quantifying methane emissions  
36 from different sources is critical for developing strategies to reduce atmospheric methane levels. Anthropogenic  
37 emissions originate from a large number of point sources (coal mine vents, oil/gas facilities, livestock operations,  
38 landfills, wastewater treatment plants) that are individually small, spatially clustered, often intermittent, and difficult to  
39 quantify (Allen et al., 2013; Frankenberg et al., 2016). Here we investigate the unique potential of new-generation  
40 satellite instruments designed to map the Earth's surface (imaging spectrometers) to also detect methane point sources  
41 in the shortwave infrared (SWIR).

42 There has been considerable interest in using SWIR satellite observations of atmospheric methane columns by  
43 solar backscatter to detect methane sources and test emission inventories (Jacob et al., 2016). These observations are  
44 traditionally made by atmospheric sensors with high spectral resolution (<1 nm) to capture the fine structure of  
45 methane absorption lines (Table 1). The requirement of high spectral resolution has generally implied a coarse pixel  
46 resolution (>1 km) to achieve satisfactory signal-to-noise ratios (SNR), but this limits the ability to localize and  
47 quantify individual point sources. Inverse analyses of observations from the SCIAMACHY instrument with 60 km  
48 pixel resolution, and from the GOSAT instrument with sparse sampling at 10 km pixel resolution, have quantified  
49 emissions over regional scales (Bergamaschi et al., 2009; Kort et al., 2014; Turner et al., 2015). The recently launched  
50 TROPOMI instrument with global daily coverage at 7 km pixel resolution (Hu et al., 2018) will refine the regional  
51 characterization but still cannot resolve point sources (Sheng et al., 2018). Planned instruments with ~1 km pixel  
52 resolution (MethaneSat, Proppe et al., 2017; Geo-FTS, Xi et al., 2016) should be able to detect large point sources after  
53 inversion of several days of observations (Cusworth et al., 2018; Turner et al., 2018) but would not resolve densely  
54 clustered or temporally variable sources.

55 Atmospheric sensors for methane generally focus on achieving high precision (<1%) and low relative bias  
56 (<0.3%), appropriate for regional characterization of sources (Buchwitz et al., 2015). However, these requirements can  
57 be relaxed if the focus is to observe individual plumes. Precision can be traded for pixel resolution because methane  
58 plumes are generally sub-kilometer in scale (Frankenberg et al., 2016), so that plume enhancements are larger when the  
59 pixel resolution is finer (Jacob et al., 2016). In a theoretical simulation study for the GHGSat microsatellite instrument



60 with  $50 \times 50 \text{ m}^2$  pixel resolution, Varon et al. (2018a) found that a 1-5% precision would be adequate for single-pass  
61 observation of plumes to quantify point sources of magnitude  $\sim 100 \text{ kg h}^{-1}$ . This would account for most of the total  
62 methane emitted by point sources in the United States reporting to the Greenhouse Gases Reporting Program (Jacob et  
63 al., 2016). A demonstration GHGSat instrument (GHGSat-D) launched in 2016 with an estimated precision of 13%  
64 limited by instrument imperfections, has proven able to detect large point sources in excess of  $1000 \text{ kg h}^{-1}$  (Varon et al.,  
65 2018b).

66 Here we examine the potential of a different class of satellite instruments, imaging spectrometers, to provide  
67 global snapshots of individual methane point sources. These instruments are designed for global coverage of land  
68 surfaces, but they may be used for atmospheric sensing as well. They have fine spatial sampling, or pixel resolution  
69 ( $< 100 \text{ m}$ ), with coarser spectral sampling to measure vibrational overtone absorptions in surface reflectance. Some  
70 current imagers such as Landsat (Roy et al., 2014) and WorldView-3 (<http://worldview3.digitalglobe.com>) have  
71 observing bands in the SWIR intended to infer soil moisture, mineral composition, and vegetation traits (Cleemput et  
72 al., 2018). However, the SWIR spectral resolutions for Landsat (100 nm) and WorldView-3 (40-50 nm) are too coarse  
73 to usefully observe methane. The Hyperion instrument onboard NASA Earth Observing-1 had 10 nm spectral  
74 resolution in the SWIR but a very low signal to noise ratio (SNR) of 20 (Folkman et al., 2001).

75 A new generation of imaging spectrometers set for launch over the next few years (EnMAP, PRISMA, EMIT,  
76 and an anticipated SBG investigation) will achieve  $\sim 10 \text{ nm}$  or better spectral resolution in the SWIR with pixel  
77 resolution in the range 30-60 m and SNR of 180-400 or beyond (Table 1). Experience with airborne imaging  
78 spectrometers of comparable specifications suggests that these satellite instruments should be able to usefully observe  
79 methane plumes. The Airborne Visible/Infrared Imaging Spectrometer (AVIRIS-C), with a 10 nm spectral resolution  
80 and SNR of 70 (Green et al., 1998), was able together with Hyperion to detect the massive Aliso Canyon methane leak  
81 in California (Thompson et al., 2016). The next generation AVIRIS instrument (AVIRIS-NG), with a finer spectral  
82 resolution of 5 nm and SNR of 200 (Thorpe et al., 2014), was able to detect a range of methane plumes over the Four  
83 Corners region of New Mexico including from gas processing facilities, storage tanks, pipeline leaks, well pads, and  
84 coal mine venting shafts (Frankenberg et al., 2016). AVIRIS-NG was flown over 272000 potential methane emitting  
85 facilities in California between 2016 and 2018 (CARB, 2017).

86

87 **2 Imaging spectrometer spectra including methane plumes**



88        The next generation of spaceborne imaging spectrometers in Table 1 includes PRISMA (launched March  
89        2019), EnMAP (2020), EMIT (2022), SBG (2025-2027). The AMPS instrument (proposed) would bridge the gap  
90        between surface imagers and methane sensors, by providing 1 nm SWIR spectral resolution while maintaining 30 m  
91        spatial resolution (Thorpe et al., 2016). We will focus our baseline analysis on EnMAP, for which detailed  
92        documentation is available (Guanter et al., 2015), and examine other instruments through sensitivity analyses. EnMAP  
93        is a push-broom style instrument with 10 nm resolution in the SWIR and an expected 180 SNR at 2300 nm. PRISMA  
94        (<http://www.prisma-i.it/>) has very similar instrument specifications as EnMAP. The EMIT instrument will fly on the  
95        International Space Station. It is slated to have a 7-10 nm spectral resolution and 60 m pixel resolution (Green et al.,  
96        2018). Other investigations, such as SBG, are called for in the NASA Earth Science and Applications Decadal Survey  
97        (National Academies, 2018).

98        Figure 1 shows simulated transmission spectra in the weak (~1650 nm) and strong (~2300 nm) SWIR methane  
99        absorption bands at the spectral resolutions of TROPOMI (0.25 nm FWHM), AVIRIS-NG (5 nm), and EnMAP (10  
100       nm). EnMAP spectra are sampled following the precise wavelength positions given in Guanter et al. (2015). The 1650  
101       nm methane band has the advantage of being near a CO<sub>2</sub> band, so that joint retrievals of methane and CO<sub>2</sub> can be  
102       combined with independent knowledge of the CO<sub>2</sub> column mixing ratio to remove joint errors in surface reflectivity  
103       and atmospheric scattering (the so-called “CO<sub>2</sub> proxy” method; Frankenberg et al. 2005a). However, the 1650 nm band  
104       is much weaker than the 2300 nm band and only the 2v Q-branch could be detected at coarser spectral resolution.  
105       Sampling the transmission spectra at the EnMAP spectral resolution yields only 8 data points in the 1650 nm band as  
106       compared to 25 in the 2300 nm band. The 2300 nm band also exhibits more resolved structure. Our early attempts to  
107       use the CO<sub>2</sub> proxy method in the 1650 nm band with EnMAP synthetic spectra were unsuccessful. In what follows we  
108       focus on the 2300 nm band as sampled in the useful 2210 - 2410 nm range.

109       We examined the sensitivity of EnMAP to atmospheric methane variability by generating synthetic top of  
110       atmosphere (TOA) EnMAP scenes with variable methane over a variety of surface types. We used for this purpose the  
111       EnMAP End-to-End Simulation Tool (EeteS; Segl, 2012), developed to generate EnMAP TOA spectra with expected  
112       instrument error included. EeteS takes surface information from another imaging instrument (e.g., SPOT-5), and passes  
113       the image through spatial, atmospheric, spectral, and radiometric modules to generate EnMAP spectra. The  
114       atmospheric module is based on the MODTRAN5 radiative transfer code. It assumes a horizontally invariant 1800 ppb  
115       dry air column methane mixing ratio ( $X_{\text{CH}_4}$ ) and here we add methane plumes simulated with the Weather and Research  
116       Forecasting Model Large Eddy Simulation (WRF-LES) at 30 × 30 m<sup>2</sup> resolution (Varon et al., 2018a).



117       Figure 2 shows a simulated red-blue-green (RGB) EeteS image over Berlin. We consider four scenes within  
118   this domain to add WRF-LES methane plumes and perform subsequent retrievals. The scenes - Grass, Dark (water),  
119   Bright, Urban - have mean SWIR surface reflectances of 0.09, 0.02, 0.30, 0.13, respectively. The urban scene is highly  
120   heterogeneous. The WRF-LES simulation is conducted with  $30 \times 30 \text{ m}^2$  resolution (the EnMAP pixel resolution), 100  
121    $\text{W m}^{-2}$  sensible heat flux (moderately unstable meteorological conditions), and a mean wind speed of  $3.5 \text{ m s}^{-1}$ . We  
122   generate an ensemble of 15 instantaneous plumes by sampling the WRF-LES simulation at five time slices and for  
123   three source rates of 100, 500, and  $900 \text{ kg h}^{-1}$ . This range is typical of large (but not unusually large) point sources  
124   (Jacob et al., 2016).

125       We compute the optical depth of the methane plume  $\tau(\lambda)$  at wavelength  $\lambda$  by multiplying HITRAN absorption  
126   cross sections ( $\sigma_H$ ; Kochanov et al., 2016) by the methane mixing ratio enhancement ( $\Delta VMR$ ) and density of dry air  
127   ( $VCD$ ) in the 72-layered atmosphere of the MERRA-2 meteorological reanalysis (Gelaro et al., 2017):

$$128 \quad \tau(\lambda) = \sum_{i=1}^{72} \Delta VMR_i VCD_i \sigma_{H,i}(\lambda). \quad (1)$$

129  
130       The plume transmission  $T(\lambda)$  is the negative exponential of  $\tau(\lambda)$  weighted by the geometric airmass factor  $A$  (AMF) for  
131   the backscattered solar radiation:

$$132 \quad T(\lambda) = \exp\{-A\tau(\lambda)\}. \quad (2)$$

133

134  
135       Each pixel's EeteS radiance spectrum is multiplied by this additional plume transmission. We do not add noise or  
136   aerosol effects to the plume transmission spectra because the EeteS scene already accounts for those in the computation  
137   of back-scattered radiances, and the plume transmission is just a multiplicative factor on these back-scattered radiances.  
138       Figure 3 shows an example WRF-LES plume ( $500 \text{ kg h}^{-1}$  source rate) superimposed over the Grass and Urban scenes.

139       EnMAP has a specific spectral resolution and SNR. We examined the sensitivity of the retrieval to these  
140   parameters by generating synthetic spectra for different spectral resolutions and SNRs, thus extending our analysis to  
141   other new-generation imaging spectrometers (Table 1). For this purpose, we interpolated EeteS surface radiance spectra  
142   to the desired spectral resolution assuming no instrument noise. We then multiplied these radiance spectra by the  
143   standard atmosphere plus WRF-LES plume transmission spectra and added uncorrelated instrument noise as per the  
144   specified SNR.



145 To test our EnMAP retrievals on actual data, we also downsampled AVIRIS-NG images taken from aircraft  
146 over California (CARB, 2017) to match EnMAP spatial resolution, and further convolved these spectra with a 10 nm  
147 Gaussian filter to match EnMAP spectral resolution and wavelength positions. AVIRIS-NG flew at 3-4 km above the  
148 ground, so we simulated additional extinction at higher altitudes based on the U.S standard atmosphere (Kneizys et al.,  
149 1996). We compared the retrieved methane from AVIRIS-NG and the synthetic EnMAP to determine the ability of  
150 EnMAP to detect and quantify the methane point sources identified by AVIRIS-NG.

151

### 152 **3 Methane retrieval**

153 We retrieved methane from the synthetic imaging spectrometer spectra by adapting the Iterative Maximum A  
154 Posteriori - Differential Optical Absorption Spectroscopy (IMAP-DOAS) algorithm developed for AVIRIS  
155 (Frankenberg et al., 2005b; Thorpe et al., 2017; Ayasse et al., 2018). DOAS retrievals isolate higher frequency features  
156 resulting from gas absorption from lower frequency features that include surface reflectance as well as Rayleigh and  
157 Mie scattering (Bovensmann et al., 2011). A polynomial term accounts for the low frequency features (Thorpe et al.,  
158 2017).

159

#### 160 *3.1 State vector*

161 In addition to methane ( $\text{CH}_4$ ), the retrieval must account for variable absorption by water vapor ( $\text{H}_2\text{O}$ ) and  
162 nitrous oxide ( $\text{N}_2\text{O}$ ) over the 2210-2400 nm spectral region. We parameterize low frequency spectroscopic features as a  
163 sum of Legendre polynomials of order  $k = [0, K]$  with coefficients  $a_k$ . The state vector ( $\mathbf{x}$ ) optimized through the  
164 retrieval is therefore composed of the following elements:

165 
$$\mathbf{x} = (s_{\text{CH}_4}, s_{\text{H}_2\text{O}}, s_{\text{N}_2\text{O}}, a_0, \dots, a_K)$$

166 where  $s$  is a scaling factor applied to the column mixing ratio of each gas from the U.S standard atmosphere (Kneizys et  
167 al., 1996). We do not include aerosols in the retrieval as they play little role at the relevant spatial and spectral  
168 resolution (Ayasse et al., 2018). Methane point sources generally do not co-emit aerosols.

169

#### 170 *3.2 Optimal estimation*

171 To retrieve the state vector from the Eetes TOA radiances, we use a forward model similar to previous IMAP-  
172 DOAS algorithms (Thorpe et al., 2017, Ayasse et al., 2018), with a modification to the polynomial term for surface  
173 reflectance:



174                   
$$F^h(\mathbf{x}, \lambda) = I_0(\lambda) \exp \left( -A \sum_{n=1}^3 s_n \sum_{l=1}^{72} \tau_{n,l} \right) \sum_{k=0}^K a_k P_k(\lambda) \quad (3)$$

175       Here  $F^h$  is the high-resolution backscattered TOA radiance at wavelength  $\lambda$ ,  $I_0(\lambda)$  is the incident TOA solar intensity,  
 176        $\tau_{n,l}$  is the default optical depth from the US standard atmosphere for trace gas element  $n = [1,3]$  of the state vector at  
 177       vertical level  $l = [1,72]$ ,  $s_n$  is the scaling factor to that default optical depth optimized in the retrieval,  $P_k(\lambda)$  is the  $k^h$   
 178       Legendre polynomial, and the  $a_k$  are coefficients optimized in the retrieval. The optical depth  $\tau_{n,l}$  is computed in the  
 179       same fashion as Equation 1, using information from the MERRA-2 reanalysis and HITRAN absorption cross sections.  
 180       For satellite retrievals, the AMF is a scalar describing the optical path through the atmosphere. In Section 4.3, we apply  
 181       the IMAP-DOAS algorithm to airborne AVIRIS-NG scenes and use a vector-valued AMF that depends on the height of  
 182       the aircraft.

183               Previous IMAP-DOAS algorithms used a simple polynomial approximation for the surface reflectance, but  
 184       here we use Legendre polynomials to exploit their orthogonality. We find that  $K = 4$  provides sufficient spectral  
 185       resolution whereas previous applications using simple polynomials required  $K = 6$  (Ayasse et al., 2018).

186               We compute the TOA backscattered radiances  $F^h(\mathbf{x}, \lambda)$  over the 2210-2410 nm spectral range at 0.02 nm  
 187       resolution, and assemble these in a vector  $\mathbf{F}^h(\mathbf{x})$  representing the high-resolution spectrum as simulated by the forward  
 188       model for a given  $\mathbf{x}$ . We convolve this spectrum with the instrument FWHM and then sample at the known wavelength  
 189       positions. For example, for EnMAP, we convolve  $\mathbf{F}^h(\mathbf{x})$  with a 10 nm FWHM and sample the resulting spectra at  
 190       EnMAP's 10 nm intervals to get the low-resolution  $\mathbf{F}(\mathbf{x})$ . We also explored performing separate convolutions on the  
 191       high resolution transmission and polynomial terms in Equation 3, and then multiplying them together to get  $\mathbf{F}(\mathbf{x})$ . We  
 192       found little difference in the results between methods.

193               Observed backscattered TOA radiances ( $\mathbf{y}$ ) can be represented as

194                   
$$\mathbf{y} = \mathbf{F}(\mathbf{x}) + \boldsymbol{\epsilon} \quad (4)$$

195       where the observational error  $\boldsymbol{\epsilon}$  is the sum of instrument and forward model errors. As is commonly done for satellite  
 196       retrievals, we assume that the forward model error is small compared to the instrument error characterized by the SNR.  
 197       The forward model is non-linear so that the solution must be obtained iteratively. A Jacobian matrix is calculated for  
 198       each iteration of the state vector

199                   
$$\mathbf{K}_i = \frac{\partial \mathbf{F}}{\partial \mathbf{x}} \Big|_{\mathbf{x}=\mathbf{x}_i} \quad (5)$$

200       and we employ a Gauss-Newton iteration to solve iteratively for the optimal state vector (Rodgers, 2000):



201                    $\mathbf{x}_{i+1} = \mathbf{x}_A + (\mathbf{K}_i^T \mathbf{S}_0^{-1} \mathbf{K}_i + \mathbf{S}_A^{-1})^{-1} \mathbf{K}_i^T \mathbf{S}_0^{-1} [y - \mathbf{F}(\mathbf{x}_i) + \mathbf{K}_i(\mathbf{x}_i - \mathbf{x}_A)] \quad (6)$

202 Here  $\mathbf{S}_0 = [\mathbf{\epsilon}\mathbf{\epsilon}^T]$  is the observation error covariance matrix defined by the instrument SNR,  $\mathbf{x}_A$  is the prior estimate of the  
203 state vector, and  $\mathbf{S}_A$  is the prior error covariance matrix. We set a weak prior error variance for methane,  $\sigma_{CH_4}^2 = 5$ , to  
204 accommodate large plume enhancements. The prior  $X_{CH_4}$  estimate is 1800 ppb. The iterative analytical solution to the  
205 inverse problem as described by equation (6) also provides the posterior error covariance matrix ( $\hat{\mathbf{S}}$ ) as part of the  
206 solution:

207                    $\hat{\mathbf{S}} = (\mathbf{K}_i^T \mathbf{S}_0^{-1} \mathbf{K}_i + \mathbf{S}_A^{-1})^{-1} \quad (7)$

208

209  $\hat{\mathbf{S}}$  gives information on the error correlation between retrieved methane and surface reflectivity, which is a major  
210 concern for methane retrievals (Butz et al., 2012).

211

#### 212 **4. Results and Discussion**

##### 213 *4.1 EnMAP plume retrievals over different surfaces*

214 Figure 3 shows examples of the IMAP-DOAS retrievals of 500 kg h<sup>-1</sup> and 900 kg h<sup>-1</sup> WRF-LES plumes over  
215 the Grass and Urban scenes. Near the emission source, the 500 kg h<sup>-1</sup> plume is clearly defined in the Grass scene. It is  
216 also detectable in the Urban scene but obscured by surface retrieval artifacts. The 900 kg h<sup>-1</sup> plume is better captured  
217 over both surfaces, though major retrieval artifacts remain in the Urban scene.

218 Varon et al. (2018a) previously estimated the theoretical ability of a satellite instrument to quantify source  
219 rates from point sources as a function of instrument precision, assuming a uniform surface reflectance. They concluded  
220 that an instrument with 1-5% precision on  $X_{CH_4}$  would be able to quantify point sources with an error of 70-170 kg h<sup>-1</sup>.  
221 Here we characterize the EnMAP instrument precision as the relative root-mean squared-error (RRMSE) between the  
222 true and retrieved column methane concentrations for individual 30 × 30 m<sup>2</sup> pixels in the scenes of Figure 2 including  
223 the WRF-LES plumes. Figure 4 summarizes the results for the four scenes of Figure 2. We find precisions of 8.2 ±  
224 0.7% for Grass, 13 ± 0.7% for Urban, and 3.7 ± 0.5% for Bright scenes. The standard deviations refer to the RRMSEs  
225 computed for the 15 different realizations of the WRF-LES plumes and for the 3 source rates of 100, 500, and 900 kg h<sup>-</sup>  
226 <sup>1</sup>. The Dark scene was consistently unsuccessful, with error of at least 100% for each realization, and we do not discuss  
227 it further. The Bright scene performs the best because of the large backscattered photon flux. The Urban scene performs  
228 worse than the Grass scene, even though its average SWIR surface reflectance is larger, due to the larger variability in



229 reflectance over the scene including dark pixels. As illustrated in Figure 3, the 8% precision over the relatively uniform  
230 grass surface should enable EnMAP to successfully quantify 500 kg h<sup>-1</sup> point sources in a single pass.

231 Beyond the precision for the methane retrieval, an additional limitation for retrieving point sources is the error  
232 correlation with variable surface reflectance. This is illustrated in Figure 3 with the retrieved  $X_{\text{CH}_4}$  enhancements over  
233 Grass and Urban scenes relative to the background. In the case of the Grass scene with a 500 kg h<sup>-1</sup> source, the 8%  
234 precision limits the ability to observe the downwind plume but there is a clear enhancement over background at the  
235 source location. With a 900 kg h<sup>-1</sup> source the downwind plume becomes well-defined against the background. In the  
236 case of the Urban scene, the detection of the 500 kg h<sup>-1</sup> plume is far more problematic because of large positive artifacts  
237 over dark (water) pixels. The 900 kg h<sup>-1</sup> plume is still difficult to distinguish from the artifacts and would require prior  
238 knowledge of source location to be identified and quantified. The error correlation between methane and surface  
239 reflectance in the retrieval can be reduced by increasing the spectral resolution of the instrument as discussed in Section  
240 4.2.

241

#### 242 *4.2 Sensitivity to instrument spectral resolution and SNR*

243 Here we examine the potential of future instruments with improved spectral resolution and SNR relative to  
244 EnMAP (Table 1) to achieve improved retrievals of point sources. Figure 5 shows the change in retrieval precision as  
245 we vary the spectral resolution from 10 to 1 nm and the SNR from 100 to 500. The precision estimates are calculated  
246 using two methods. First, we estimate the precision by evaluating the RRMSEs averaged over the Grass, Urban, and  
247 Bright scenes of Figure 2, for 3 source rates and 15 instantaneous plume realizations, following the procedure of  
248 Section 4.1. Since SNR varies on a per-pixel basis, the plotted SNRs for this method represent the mean scene SNR.  
249 Specifications of the instruments in Table 1 are identified on the plot. Precision improves as spectral resolution and  
250 SNR increase, as expected. The dependencies are not linear, and the contours are concave, meaning that precision is  
251 more effectively improved by increasing spectral resolution by a certain factor than by increasing SNR by the same  
252 factor. Increasing the spectral resolution improves precision through multiple independent factors: by increasing the  
253 number of independent measurements across the methane interval; by increasing the effective squared depth of the  
254 sharpest methane absorptions, for improved spectral contrast relative to the continuum; and by better resolution of the  
255 unique methane absorption shape, which improves discrimination against potential surface confusers.

256 Second, we estimate theoretical precision in Figure 5 by extracting the associated  $X_{\text{CH}_4}$  posterior error  
257 covariance term of  $\hat{\mathbf{S}}$  from Equation 7. Here we find that instrument precision improves more as a function of SNR than



258 spectral resolution, which is a different result than the first precision method. Issues with the surface retrieval drive the  
259 contrasting results between the two methods. This underscores the difficulty in assigning a single retrieved  $X_{\text{CH}_4}$   
260 uncertainty value for different instrument configurations. For a spaceborne AVIRIS-NG instrument, multiple along-  
261 track samples would increase the SNR as a function of  $\sqrt{N}$ , where  $N$  = number of along-track frames. For the second  
262 precision method, doing multiple along-track samples improves the theoretical precision from 5% to 1%. Varon et al.  
263 (2018a) found that an instrument with 5% precision could constrain most anthropogenic point sources above 170 kg h<sup>-1</sup>.  
264 Using both the RRMSE and theoretical precision methods of Figure 5, we find that a spaceborne AVIRIS-NG  
265 instrument (spectral resolution 5 nm, SNR 200-400) would have a precision of 5.5 – 1.0%, meaning that such an  
266 instrument could constrain a majority of anthropogenic methane point sources.

267 A benefit of increasing spectral resolution is to improve decoupling of surface and methane spectroscopic  
268 features. We saw in Figure 3 that this was a major source of error over inhomogeneous surfaces such as the Urban  
269 scene. It is manifested in the retrieval by an error correlation between state vector elements  $s_{\text{CH}_4}$  (scaling factor for  
270 methane column mixing ratios) and  $a_k$  (coefficients for the surface reflectivity described by Legendre polynomials).  
271 This error correlation is described by the posterior error covariance matrix  $\hat{\mathbf{S}}$  obtained as part of the retrieval (Equation  
272 6). For example, the error correlation decreases significantly between EnMAP ( $r = -0.33$ ) and AMPS ( $r = -0.19$ ). This  
273 driven by the increase in spectral resolution from 10 nm to 1 nm. A separate test shows that simply increasing the SNR  
274 to 300 (as for SBG) does not improve the error correlation.

275 An important implication of decoupling  $X_{\text{CH}_4}$  from the surface reflectance in the retrieval is to improve the  
276 capability for plume pattern recognition, which is necessary to convert observed plume methane enhancements into  
277 source rates (Varon et al., 2018a). Figure 6 illustrates this for the Grass and Urban scenes of Figure 3 including the  
278 plume from the 500 kg h<sup>-1</sup> point source. Following Varon et al. (2018a), we define the plume for the retrieved scenes  
279 with a plume mask that applies median and Gaussian filters to pixels above the 80<sup>th</sup> percentile of  $X_{\text{CH}_4}$  within the scene.  
280 Retrievals are performed with the specifications of the EnMAP instrument (10 nm spectral resolution, SNR 180), SBG  
281 (10 nm, 300), and AMPS (1 nm, 400).

282 For the Grass scene we find that all three instruments can discern the plume pattern near the emission source  
283 and separate it from surface features. SBG and AMPS capture larger plume domains because of their higher precisions  
284 (Figure 5), but a source rate can still be estimated successfully with EnMAP by taking into account the dependence of  
285 the retrieved plume extent on instrument precision (Varon et al., 2018a). For the Urban scene, EnMAP plume detection  
286 is swamped by surface artifacts. Simply increasing the SNR as in the SBG instrument does not improve the situation.



287 Increasing the spectral resolution to 1 nm as in the AMPS instrument enables detection of the plume though  
288 quantification would still be prone to surface artifacts.

289

290 *4.3 Evaluation with AVIRIS-NG observations*

291 To test the EnMAP retrieval capability with actual observations, we downsampled AVIRIS-NG spectra taken  
292 over California methane emitting facilities (CARB, 2017). We chose three scenes observed by AVIRIS-NG on  
293 different days over oil and gas facilities. Figure 7 shows the RGB images, the AVIRIS-NG plume retrievals performed  
294 by applying the method of Section 3 with a variable AMF, and the downsampled EnMAP retrievals. Plume masks  
295 have been applied in the same way as for Figure 6. At the altitudes used for the California survey, AVIRIS-NG has  $3 \times 3$   
296 m<sup>2</sup> pixel resolution and hence features much sharper methane enhancements than EnMAP (note the different scales for  
297 the middle and right panels).

298 We see from Figure 7 that EnMAP is able to detect the same plumes as AVIRIS-NG (two plumes in the  
299 bottom panels). This is facilitated by the brightness of the surfaces. The surface reflectivities retrieved simultaneously  
300 with the methane enhancements in our IMAP-DOAS algorithm are 0.39–0.49, brighter than the Bright EeteS scene in  
301 Section 4.1.

302 The plume observations can be related to the corresponding source rates by computing the integrated mass  
303 enhancements (IME) within the plume mask (Frankenberg et al., 2016; Varon et al., 2018a). The IME is calculated as:

304 
$$IME = \sum_{i=1}^N \Delta\Omega_i \Lambda_i \quad (7)$$

305 where  $\Delta\Omega_i$  is the plume mass enhancement in pixel  $i$  relative to background (kg m<sup>-2</sup>),  $\Lambda_i$  is the corresponding area of  
306 the pixel, and the summation is over the  $N$  pixels within the plume mask. The point source rate  $Q$  is then inferred from  
307 the IME as (Varon et al., 2018a)

308 
$$Q = \frac{U_{eff}}{L} IME \quad (8)$$

309 where  $L = \sqrt{\sum_{i=1}^N \Lambda_i}$  is a characteristic plume size and  $U_{eff}$  is an effective wind speed describing the rate of turbulent  
310 dissipation of the plume ( $L/U_{eff}$  is the lifetime of the plume against turbulent dissipation to below the detection limit).  
311 Varon et al. (2018a) relate  $U_{eff}$  to the 10-m wind speed ( $U_{10}$ ) by fitting to WRF-LES simulations. Here we use their  
312 relationship derived for the a 50 m pixel resolution, 5% precision instrument (Varon et al., 2018), and apply it as a  
313 rough approximation to the AVIRIS-NG and downsampled EnMAP plumes:

314 
$$U_{eff} = 1.1 \log U_{10} + 0.6 \quad (9)$$



315 where  $U_{eff}$  and  $U_{10}$  are in units of [m s<sup>-1</sup>]. We obtain  $U_{10}$  from the HRRR-Reanalysis at 3-km hourly resolution  
316 (<https://rapidrefresh.noaa.gov/>).

317 Figure 7 shows the source rates inferred from the AVIRIS-NG and EnMAP retrievals for each point source.  
318 The AVIRIS-NG source rates are a factor of 1.2-3.0 greater (average 1.9) than the EnMAP source rates. There could be  
319 several factors behind this discrepancy including error correlation with surface reflectivity in the EnMAP retrieval that  
320 would cause some loss of the plume, and use of a generic plume mask and IME algorithm for both instruments. As  
321 pointed out by Varon et al. (2018a), the  $U_{10}$ - $U_{eff}$  relationship needs to be tailored to the pixel resolution and precision of  
322 the particular instrument, and to the choice of plume mask. Nevertheless, the results do confirm that EnMAP should be  
323 able to detect plumes and quantify source rates down to ~100 kg h<sup>-1</sup> when the scene is sufficiently bright.

324

## 325 **5 Conclusions**

326 We examined the potential of next-generation spaceborne imaging spectrometers (EnMAP, PRISMA, EMIT,  
327 SBG,) for observing atmospheric methane plumes from point sources and inferring the corresponding source rates.  
328 These instruments have launch dates of 2019-2025 and focus on observing the Earth surface with fine pixel resolution  
329 (30 × 30 m<sup>2</sup>), but they also have observing channels at 2200-2400 nm with 7-10 nm spectral resolution that could be  
330 used to retrieve methane plumes. This would achieve much finer spatial resolution than the standard satellite  
331 instruments designed to measure atmospheric methane, and would provide a unique resource for global mapping of  
332 individual methane point sources.

333 We focused our baseline analysis on EnMAP (spectral resolution 10 nm, SNR 180, 2020 launch date) as its  
334 specifications are well documented (Guanter et al, 2015). We created synthetic spectra using the EnMAP End-to-End  
335 Simulation Tool (EeteS) to simulate various surface scenes (Grass, Urban, Bright) with instrument errors and with  
336 superimposed methane plumes generated by a WRF Large Eddy Simulation (LES). We then retrieved these scenes for  
337 atmospheric methane together with surface reflectivities using the Iterative Maximum A Posteriori - Differential  
338 Optical Absorption Spectroscopy (IMAP-DOAS) approach. The resulting precisions for methane are 8% for the Grass  
339 scene, 13% for Urban, and 4% for Bright. A 500 kg h<sup>-1</sup> methane plume (typical of very large point sources) is readily  
340 detected over the relatively homogeneous Grass surface. The highly heterogeneous Urban surface is much more  
341 challenging because of retrieval artifacts.

342 The limitation of EnMAP in detecting methane plumes over heterogeneous surfaces is caused by error  
343 correlation between methane and surface reflectivity in the retrieval. We examined how precision and error correlation



344 could be improved by increasing spectral resolution and SNR. We find that spectral resolution reduces error  
345 correlation more important than SNR. The proposed Atmospheric Methane Plume Spectrometer (AMPS), which  
346 bridges the gap between imaging spectrometers and atmospheric sensors (1 nm spectral resolution, SNR 400), can  
347 greatly decrease surface artifacts and detect a  $500 \text{ kg h}^{-1}$  plume even over the heterogeneous Urban surface. Alternative  
348 surface parameterizations might also improve  $X_{\text{CH}_4}$  and surface separation. For example, a channelwise representation  
349 with reflectances tied through an empirical covariance structure (Thompson et al., 2018) has been used previously to  
350 improve consistency in water vapor estimations. Alternative algorithms, such as matched filter approaches (Ong et al.,  
351 2019) may show different  $X_{\text{CH}_4}$  sensitivities, and in particular may be better able to represent structured reflectances of  
352 more complex surfaces.

353 We tested the EnMAP capability with actual observations by downsampling AVIRIS-NG images taken from  
354 aircraft ( $3 \times 3 \text{ m}^2$  pixels, 5 nm spectral resolution, SNR 200) over California methane emitting facilities (CARB, 2017).  
355 We showed that these EnMAP-like images are able to detect and quantify actual plumes of magnitude  $\sim 100 \text{ kg h}^{-1}$  over  
356 relatively bright surfaces. Source rates inferred from the plumes with a generic Integrated Mass Enhancement (IME)  
357 method are a factor of 1.2 to 3 lower for EnMAP than for AVIRIS-NG, which could be due in part to unaccounted  
358 dependence of the IME method on instrument pixel size and precision.

359 In summary, our analysis shows that future spaceborne imaging spectrometers designed to map the Earth  
360 surface in the SWIR also have considerable potential for detecting methane plumes from point sources and quantifying  
361 source rates. The detection capability of  $100\text{-}500 \text{ kg h}^{-1}$  over relatively bright or homogeneous land surfaces would  
362 allow accounting for a wide range of point sources. The fine spatial resolution of these instruments should make them a  
363 unique resource to contribute to tiered observing systems for greenhouse gases (Duren and Miller, 2012).

364

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**Table 1.** Shortwave infrared (SWIR) remote sensors for observing methane point sources

Instrument	Pixel size (km <sup>2</sup> )	SWIR spectral range (nm) <sup>a</sup>	Spectral resolution (nm) <sup>b</sup>	Signal-to-noise ratio (SNR) <sup>c</sup>	Observing epoch
<i>Aircraft</i>					
AVIRIS-NG <sup>d</sup>	0.003 × 0.003	1600–1700; 2200–2510	5.0	200–400 <sup>e</sup>	Campaigns
<i>Satellite</i>					
<i>Atmospheric sensors</i>					
SCIAMACHY <sup>f</sup>	30 × 60	1630–1670	1.4	1500	2002–2012
GOSAT <sup>g</sup>	10 × 10	1630–1700	0.06	300	2009–
GHGSat <sup>h</sup>	0.05 × 0.05	1600–1700	0.1	TBD	2016–
TROPOMI <sup>i</sup>	7 × 7	2305–2385	0.25	100	2017–
AMPS <sup>j</sup>	0.03 × 0.03	1990–2420	1.0	200–400	Proposed
<i>Imaging spectrometers</i>					
PRISMA <sup>k</sup>	0.03 × 0.03	1600–1700; 2200–2500	10	180	2019–
EnMAP <sup>l</sup>	0.03 × 0.03	1600–1700; 2200–2450	10	180	2020–
EMIT <sup>m</sup>	0.06 × 0.06	1600–1700; 2200–2510	7–10	200–300	2022–
SBG <sup>n</sup>	0.03 × 0.03	1600–1700; 2200–2510	7–10	200–300	2025–

<sup>a</sup>Methane has absorption bands near 1650 and 2300 nm.

<sup>b</sup>Spectral resolution is represented by the full-width at half-maximum (FWHM).

<sup>c</sup>For SCIAMACHY and GOSAT, SNR is for CO<sub>2</sub> band used in the CO<sub>2</sub>-proxy method retrieval. For other instruments, SNR is at 2300 nm.

<sup>d</sup>Airborne Visible/Infrared Imaging Spectrometer – Next Generation (Thorpe et al., 2017). AVIRIS-NG provides roughly a ground sampling distance (GSD) of 1 m per km altitude. The Frankenberg et al. (2016) and Duren et al. (2019) campaigns operated at 3–4 km altitude.

<sup>e</sup>Along-track oversampling increases SNR by  $\sqrt{N}$  where  $N$  = number of along-track frames. AVIRIS-NG routinely achieves  $N > 4$  so AVIRIS-NG effective SNR at 2300 nm can be as much as 400.

<sup>f</sup>SCanning Imaging SpectroMeter for Atmospheric CHartographY (Frankenberg et al., 2006)



<sup>g</sup>TANSO-FTS instrument aboard the Greenhouse gases Observing SATellite (Kuze et al., 2016). Pixels are circles of 10 km diameter.

<sup>h</sup>GreenHouse Gases Satellite (McKeever et al., 2017). Revisit times are for selected  $12 \times 12 \text{ km}^2$  scenes. The demonstration GHGSat-D instrument presently in space has additional instrument imperfections that limit its precision to 13% (McKeever et al. 2017).

<sup>i</sup>TROPOspheric Monitoring Instrument (Hu et al., 2018)

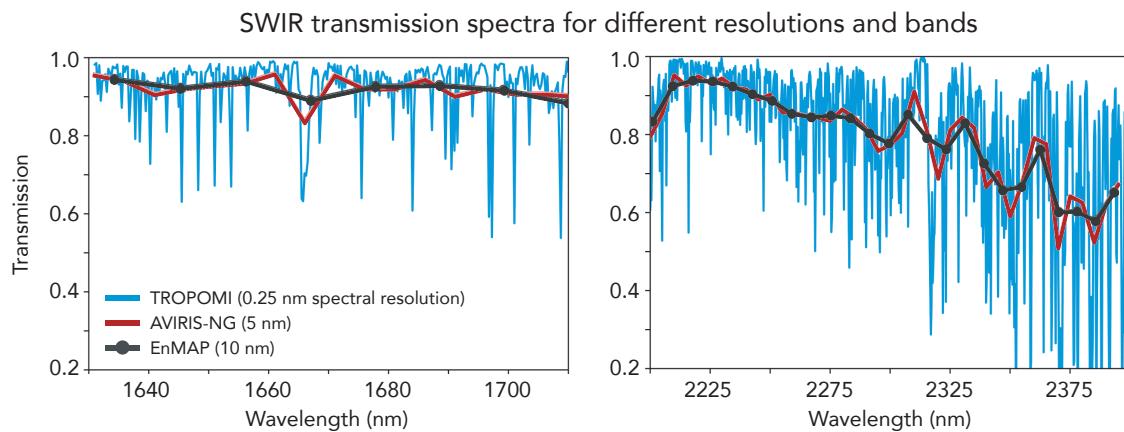
<sup>j</sup>Airborne Methane Plume Spectrometer (Thorpe et al., 2016)

<sup>k</sup>PRecursore IperSpettrale della Missione Applicativa (<http://prisma-i.it>)

<sup>l</sup>Environmental Mapping and Analysis Program (Guanter et al., 2015)

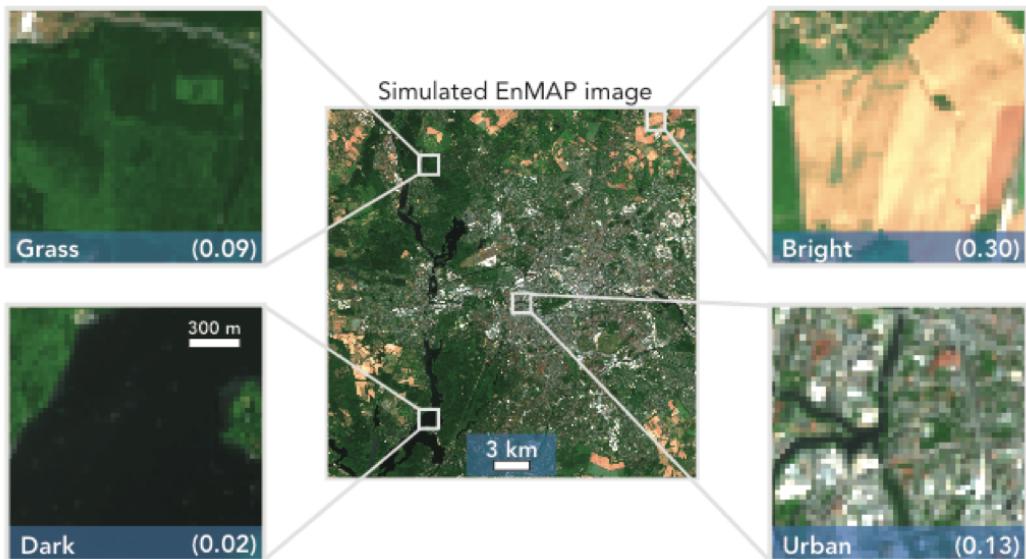
<sup>10</sup><sup>m</sup>Earth Surface Mineral Dust Source Investigation (Green et al., 2018)

<sup>n</sup>Surface Biology and Geology, previously called HyspIRI (Hochberg et al., 2015)

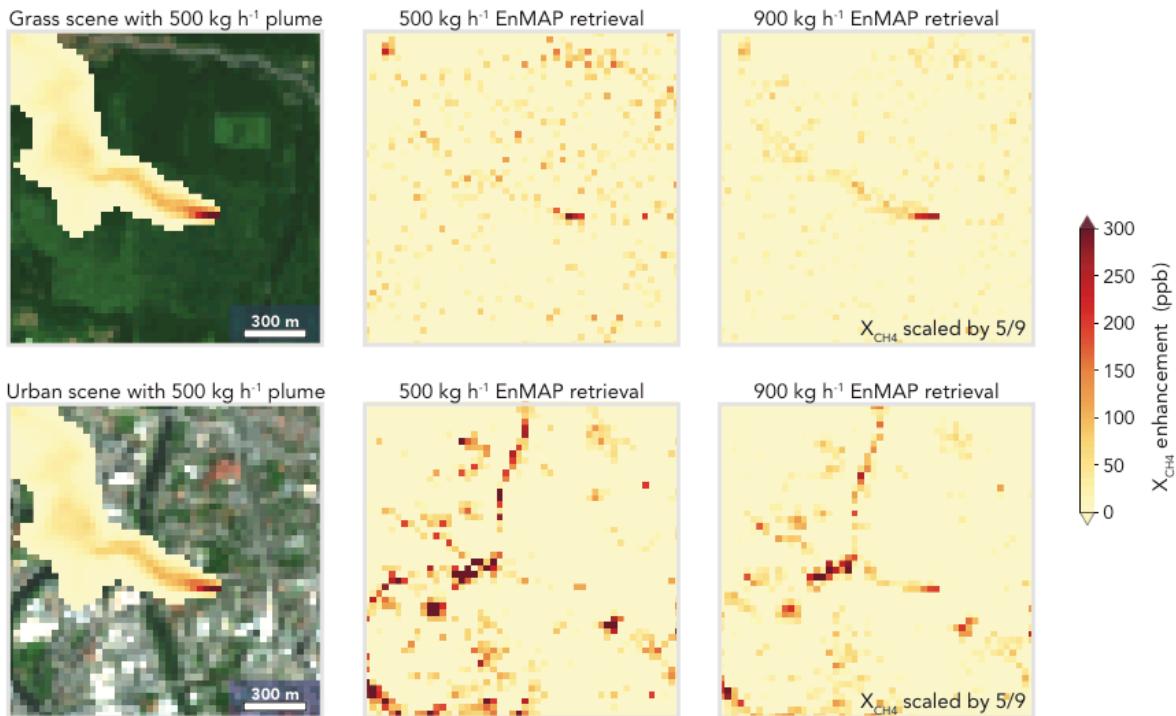


**Figure 1.** Simulated top of the atmosphere (TOA) transmission spectra for different spectral resolutions (FWHM = full-width at half-maximum) in the 1650 nm (left panel) and 2300 nm (right panel) shortwave infrared (SWIR) bands. High-resolution spectra were simulated for the U.S. Standard Atmosphere with 1800 ppb total column methane using the HITRAN spectroscopic database and the HITRAN Application Programming Interface (HAPI) tool (Kochanov et al., 2016), and were then sampled with spectral resolutions of 0.25 nm (TROPOMI), 5 nm (AVIRIS-NG), and 10 nm (EnMAP) at the appropriate wavelength positions.

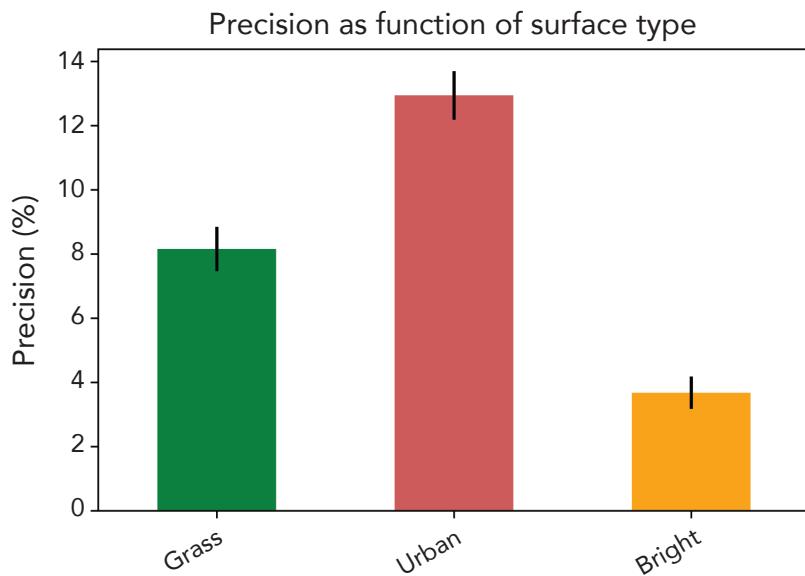
10



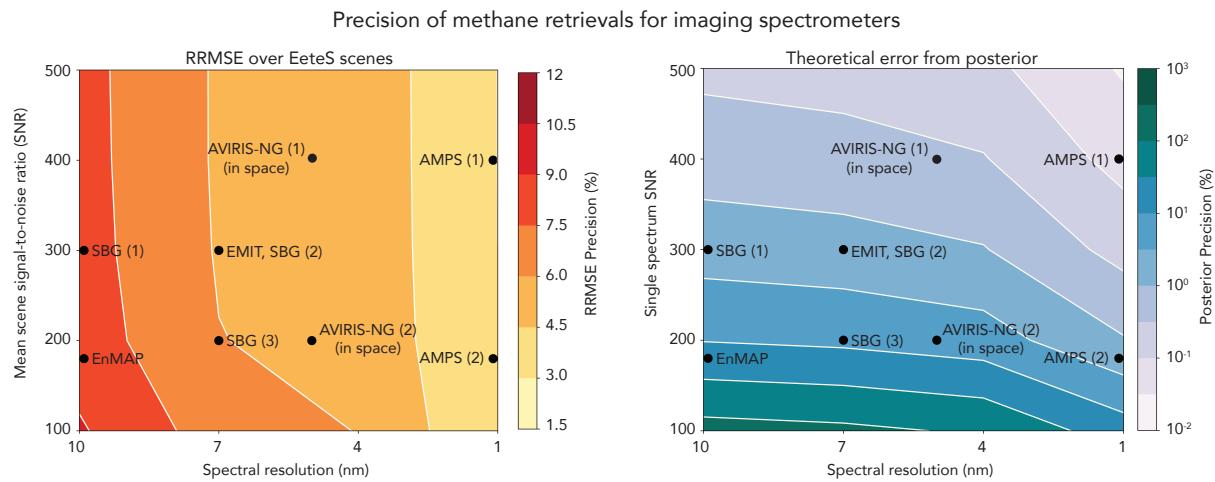
5 **Figure 2.** RGB image of a synthetic EnMAP scene simulated using the EnMAP End-to-End Simulation Tool (EetsS) over Berlin. Four scenes with 30×30 m<sup>2</sup> pixel resolution are shown (Grass, Dark, Bright, Urban) with average surface reflectances in the SWIR (2210-2410 nm) given in parentheses. These different scenes are used in Section 3 to evaluate the sensitivity of EnMAP to atmospheric methane.



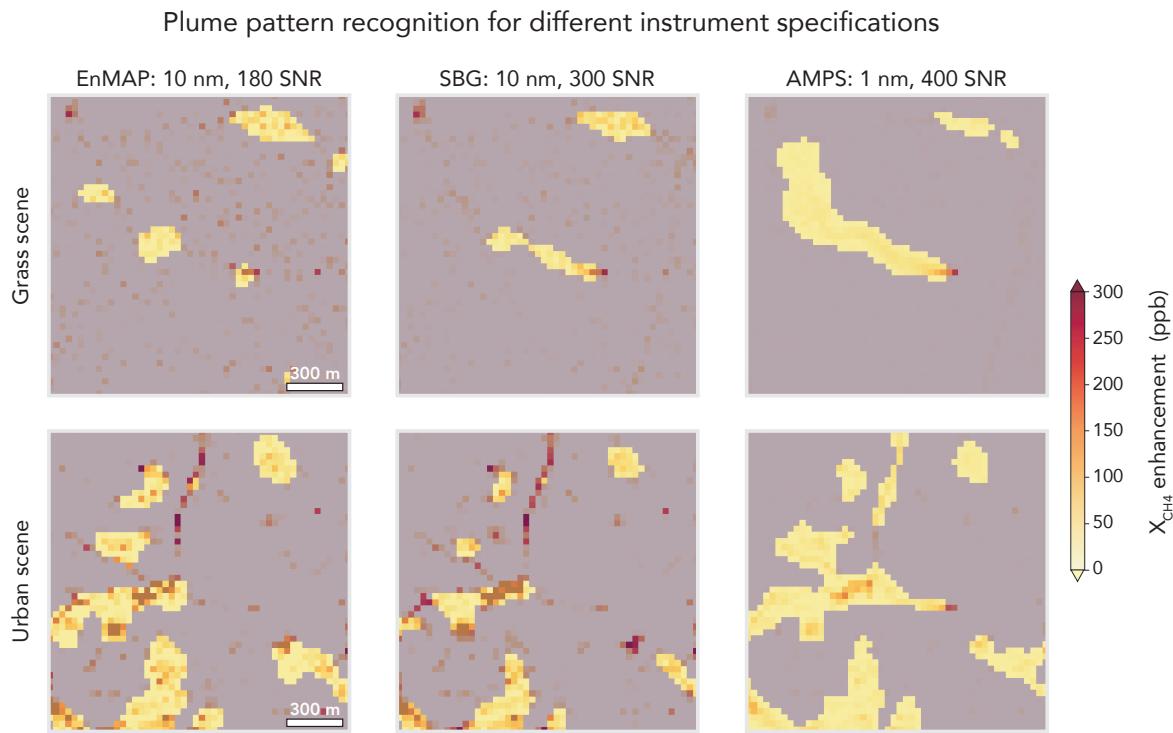
**Figure 3.** Retrieval of a methane plume over grass and urban EnMAP scenes. The plume was generated by WRF-LES with a source rate of either 500 kg h<sup>-1</sup> or 900 kg h<sup>-1</sup>. The left panels show the dry air column mixing ratio enhancements relative to the 1800 ppb background for a 500 kg h<sup>-1</sup> methane plume superimposed on the RGB images of Figure 2. The middle panels show the retrieval of those enhancements using the IMAP-DOAS retrieval algorithm applied to the EnMAP instrument specifications. The right panels show the retrieval of the 900 kg h<sup>-1</sup> plume. The  $X_{CH_4}$  enhancements in the right panels are scaled by 5/9 to be comparable with the other panels. Negative enhancements are reset to equal the background.



**Figure 4.** Precision of atmospheric methane retrievals from the EnMAP instrument (Table 1) over different surfaces. The precisions are the relative root-mean squared errors (RRMSE) between the “true” methane columns in synthetic scenes and values obtained from the IMAP-DOAS retrieval applied to the EnMAP top-of-atmosphere (TOA) backscattered radiances.  
5 The error bars represent the standard deviation over 15 WRF-LES plume realizations and 3 source magnitudes for the plume ( $100, 500, 900 \text{ kg h}^{-1}$ ).



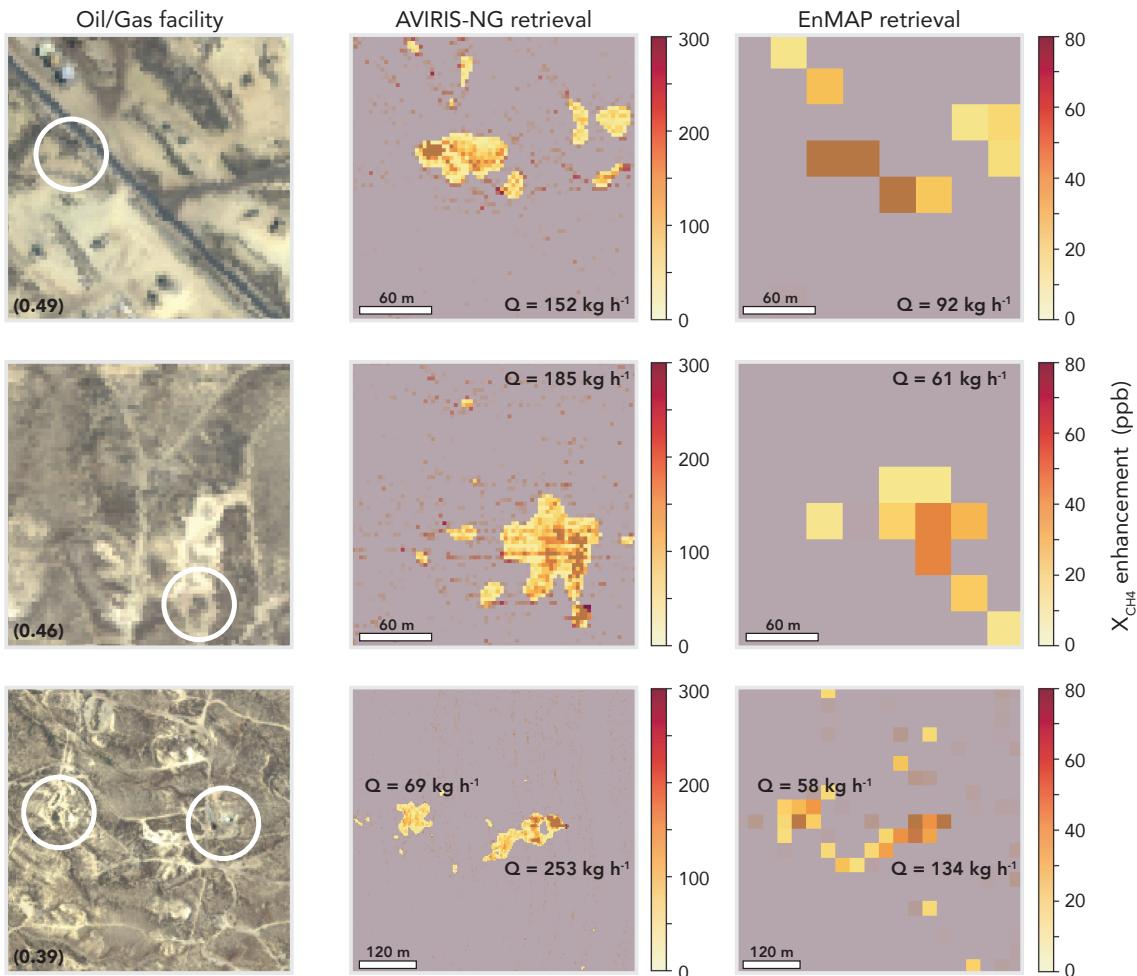
**Figure 5.** Precision of methane retrievals for spaceborne imaging spectrometers observing in the SWIR (2210–2400 nm), as a function of instrument signal-to-noise (SNR) and full-width half-maximum (FWHM) spectral resolution. The left panel shows precision expressed as the relative root-mean-square error (RRMSE) for synthetic retrievals over three scenes of Figure 2 (Grass, Urban, Bright) including a point source of 100–900 kg h<sup>-1</sup> and 15 different WRF-LES plume realizations. The SNR in the left panel represents the mean SNR over all three EeteS scenes. The right panel shows theoretical precision expressed from the posterior error covariance matrix in Equation 7. Black dots show different instrument specifications from Table 1. Specifications for the SBG and AMPS instruments are still at the design stage and values shown here are for the ranges under consideration. Results given for AVIRIS-NG are for a satellite instrument with 30×30 m<sup>2</sup> pixel resolution, with (1) or without (2) along-track oversampling, and with other specifications (spectral resolution, SNR) the same as the airborne instrument.



**Figure 6.** Plume pattern recognition applied to a point source of  $500 \text{ kg h}^{-1}$  over Grass and Urban scenes as shown in Figure 3. The plume pattern is defined by applying median and Gaussian filters to pixels above the 80<sup>th</sup> percentile of  $X_{\text{CH}_4}$  in the 5 scene. Areas excluded by the mask are shown in gray. The panels show retrievals from the EnMAP, SBG, and AMPS instruments.



### Methane retrievals over oil/gas facilities in California



**Figure 7.** Retrieval of atmospheric methane plumes from oil/gas facilities imaged by the AVIRIS-NG instrument at 3–4 km altitude over California (CARB, 2017). The left panels show the RBG images mapped by AVIRIS-NG with the oil/gas facilities of interest circled. Inset in the bottom left corner is the mean retrieved SWIR surface reflectivity for the scene. The middle panels show the IMAP-DOAS retrieval applied to the AVIRIS-NG images with  $3 \times 3 \text{ m}^2$  pixel resolution and 5 nm spectral resolution. The right panels show the IMAP-DOAS retrieval applied to spectra that were spatially and spectrally



downsampled to match EnMAP instrument specifications ( $30 \times 30 \text{ m}^2$  pixels, 10 nm spectral resolution). Note the difference in color scale for the methane enhancements in the AVIRIS-NG and EnMAP retrievals, reflecting the coarser pixel resolution of EnMAP. The plume mask is overlaid on each. The source rates for each plume obtained from the IME method are inset.