An evaluation of airborne SWIR imaging spectrometers for CH$_4$ mapping: Implications of band positioning, spectral sampling and noise

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**A B S T R A C T**

The development of instruments and methods to assist in methane (CH$_4$) emissions mapping is essential to the fossil fuel industry. Early identification of local CH$_4$ sources can benefit both petroleum hydrocarbon prospecting and environmental monitoring. Generic airborne imaging spectrometers operating in the shortwave infrared (SWIR) wavelength range (1000–2400 nm) have shown their suitability for this task. However, to date, there is no airborne scanner specifically designed for the detection of CH$_4$ plumes. To overcome current handicaps and achieve better results at local scale, further investigation in sensor design is needed to evaluate which components can be adjusted to improve CH$_4$ mapping with airborne sensors. Here, we focus on the evaluation of currently operational airborne imaging spectrometers for CH$_4$ mapping in the SWIR range. Data acquired over areas with known CH$_4$ emissions by scientific and industry-grade airborne hyperspectral sensors were examined. The research was conducted in three steps: analysis of sensor design, image processing and noise simulation. In the first step, differences in the spectral sampling between the sensors were analyzed. A reference CH$_4$ signature from HITRAN spectral database was resampled to the spectral sampling of each airborne sensor. The center wavelength of diagnostic CH$_4$ absorption features (identified in the convolved signatures) in relation to the position of band centers from each equipment was examined. For the image processing stage, a new CH$_4$ index and a classic matched filtering were used to map CH$_4$ plumes. To assess the impact of the signal-to-noise ratio (SNR) of the airborne sensors on CH$_4$ plume mapping, white noise was added to the data to simulate images with varying SNR levels. Results demonstrated that the wavelength position of band centers is a key for CH$_4$ mapping. The CH$_4$ plumes could be mapped only with scientific-grade sensors, in which the band centers were closer to the center of CH$_4$ features. Simulations with the addition of random noise demonstrated that a noisier signal is probably the reason why the industry-grade sensor tested here failed to map CH$_4$ plumes, given that all instruments have a comparable spectral sampling. Furthermore, the simulations also demonstrated that the density of the plume has also a weight on the mapping of CH$_4$ sources, once the image that captured the densest plume requested a higher addition of noise to be lost. The overall investigation indicates that a hyperspectral airborne sensor with bands properly positioned and scientific-grade SNR would better resolve the narrow CH$_4$ features in the SWIR range.

1. Introduction

Methane (CH$_4$) is a hydrocarbon gas relevant for petroleum exploration and assessing environmental impacts. CH$_4$ contributes largely to the greenhouse effect, with a global warming potential 25 times larger than carbon dioxide (CO$_2$) over a hundred years (IPCC, 2007). Observations show that CH$_4$ concentration in the atmosphere has been rising since 2007 (Saunois et al., 2016; Turner et al., 2019). Still, a hypothesis for the cause of this increase is controversial and, so far, variations in CH$_4$ emission could not be linked to a specific source. Despite uncertainties, the fossil fuel industry is estimated to be responsible for 15–20% of the global CH$_4$ budget (Schwietzke et al., 2016).

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Methane is the main component of natural gas. Mapping point sources of natural (geological) seepage and anthropogenic leakage assists the fossil fuel industry in the exploration of new sites and the identification and control of gas leaks occurring in production, transmission and handling sites. Remote sensing is an essential ally in mapping 

\[ \text{CH}_4 \] emissions and quantitative estimations of gas concentration (e. g. Asadzadeh and Souza Filho, 2017; Calin et al., 2020; Diersk and Kroll, 2017). Orbital sensors such as SCIAMACHY/ENVISAT (Bovensmann et al., 1999; Frankenberg et al., 2011) and TANSO-FTS/GOSAT (Kuze et al., 2010 and references therein), for example, provide global maps of \[ \text{CH}_4 \] and \[ \text{H}_2\text{O} \] plumes on a smaller scale (~30 to 50 m). Apart from orbital sensors, airborne spectrometers with finer spatial sampling and higher spectral resolution have also been used to detect \[ \text{CH}_4 \] sources. The Methane Airborne Mapper (MAMAP - Gerilowski et al., 2011), for example, is a non-imaging spectrometer able to retrieve column concentration and gas flux estimates from \[ \text{CH}_4 \] plumes in small scales (meters). Nevertheless, this sensor is better suited for monitoring known \[ \text{CH}_4 \] sources rather than finding unknown seeps and leaks.

\[ \text{CH}_4 \] absorption features in the infrared wavelengths (0.75–14 \( \mu \)m) allow mapping by a wide range of imaging spectrometers. Airborne sensors operating in the long and/or midwave infrared (LWIR: 7–14 \( \mu \)m and MWIR: 3–5 \( \mu \)m, respectively) such as SEBASS/MAKO (Hackwell et al., 1996; Warren et al., 2010) and HyTES (Hyperspectral Thermal Emission Spectrometer - Hook et al., 2009) were used for mapping and quantification of \[ \text{CH}_4 \] and other hydrocarbon gases (e.g. Hulley et al., 2016; Scafutto and de Souza Filho, 2019; Scafutto and Souza Filho, 2018; Tratt et al., 2014).

The detection of a gas plume in the MWIR/LWIR range relies on the thermal contrast between atmosphere and background. Quite differently, mapping \[ \text{CH}_4 \] emissions with an airborne imaging spectrometer operating in the near and shortwave-infrared (NIR/SWIR: 1.0–2.5 \( \mu \)m) is mainly based on the spectral signature of the gas. \[ \text{CH}_4 \] absorption features in this wavelength range are narrow and weak. Consequently, noise and background materials with absorption features in similar positions may hamper detection (Ayasse et al., 2018). The Airborne Visible and Infrared Spectrometer (AVIRIS) instruments (Green et al., 1988), both Classic (AVIRIS-CL) and Next Generation (AVIRIS-NG) are, to date, the only scientific-grade imaging spectrometers that have mapped \[ \text{CH}_4 \] emissions in the SWIR, both in controlled experiments, as well as in real scenarios. Some researchers managed to detect and quantify \[ \text{CH}_4 \] plumes in marine and continental environments (Bradley et al., 2011; Jongaramruengruang et al., 2019; Xiao et al., 2020), with false positives mostly related to variability in surface reflectance and surface albedo (Ayasse et al., 2018).

Considering the need to improve remote mapping of \[ \text{CH}_4 \] sources, here we evaluate three operational hyperspectral airborne imaging spectrometers for mapping \[ \text{CH}_4 \] on land: two scientific-grade sensors (JPL/NASA AVIRIS-CL and AVIRIS-NG) and an industry-grade sensor. Images acquired over areas with known \[ \text{CH}_4 \] emissions were processed and results compared to investigate the influence of band position, spectral sampling and noise on the mapping of \[ \text{CH}_4 \] plumes. This work aims to overview the technical specification of the selected airborne sensors and to analyze which features could be improved in the design of an imaging spectrometer dedicated to \[ \text{CH}_4 \] detection.

2. The \[ \text{CH}_4 \] infrared Spectrum

The infrared spectrum of \[ \text{CH}_4 \] in the SWIR wavelength range comprises two major absorption features located at (i) 1620–1720 nm and (ii) 2150–2500 nm. Both features are comprised within the so-called atmospheric windows (Fig. 1a). Between 2320–2410 nm, \[ \text{CH}_4 \] and
H₂O features overlap (Fig. 1c). In this range, the strongest CH₄ features at 2341 nm, 2348 nm and 2370 nm prevail over H₂O features between 2320–2375 nm. From 2380 nm onwards, H₂O features are significantly stronger than those of CH₄. However, CH—fundamental vibrations from which SWIR features originate are weak compared to equivalents in the MWIR and LWIR intervals (Brown et al., 2003; Dennison, 1925; Moorhead, 1932; Scafutto and Souza Filho, 2018). Therefore, due to stronger absorption and broader wavelength coverage, only the feature located between 2150–2500 nm is analyzed in this study.

3. Materials

Several images from scientific and industry-grade sensors acquired over areas with known CH₄ leaks were processed. AVIRIS-CL data (f160112t01p00r12) were acquired in January 2016 over the Aliso Canyon gas storage facility (Fig. 2b), with 6 m spatial resolution. A well blowout that occurred at that site on October 2015 resulted in a continuous release of CH₄ from an underground natural gas storage until February 2016, when the leak was capped (Thompson et al., 2016). Conley et al. (2016) estimated a leak rate of 20 metric tons of CH₄ per hour (~28,000 m³/h) at the time the AVIRIS-CL image was acquired. Two independent, CH₄ leakage field experiments (Fig. 2a) performed in Casper (WY/USA) were imaged by an industry-grade (IG) sensor in 2010 (e.g. Scafutto et al., 2018) and by the AVIRIS-NG sensor (ang20130623t201154) in 2013 (Thorpe et al., 2016). In both experiments, CH₄ plumes were simulated throughout a controlled release of variable gas rates. Leaks with higher fluxes from each experiment (23 m³/h for the IG sensor and 56.6 m³/h for AVIRIS-NG) were analyzed.

AVIRIS-NG and the IG systems acquired hyperspectral data,
4. Methods

The methodology used in this study involved three steps: (i) investigation of sensor design, where technical specifications of the three hyperspectral airborne spectrometers were analyzed; (ii) image processing, where the methods used to process the airborne images are described; and (iii) noise simulations, in which the effect of increasing noise in CH$_4$ plume detection was examined.

4.1. Analysis of sensor design

The specifications of each sensor are presented in Table 1. The IG sensor resembles AVIRIS-NG in spectral resolution. Having more bands than AVIRIS-CL, the IG sensor is considered here as an intermediate version of the two JPL/NASA sensors. To assess spectral sampling, band positioning and to perform noise simulations in the images of these sensors, a HITRAN (high resolution transmittance molecular absorption database - Gordon et al., 2017) signature of CH$_4$ (Fig. 1) was resampled to the spectral resolution and sampling interval of each imaging spectrometer (see Fig. S1 in the supplementary material). A filter-function (full width at half maximum (FWHM) of each sensor) was used for spectral resampling, in which the value at each wavelength (weight between 0 and 1) is used as a multiplicative factor when applied to the spectra being resampled (RSI, 2009).

### Table 2

| CH4I Input Bands | AVIRIS-CL | | AVIRIS-NG | | IG Sensor |
|------------------|-----------|-----------------|-----------|-----------------|------------------|
| Band number      | Wavelength (nm) | Band number      | Wavelength (nm) | Band number      | Wavelength (nm) |
| B1               | 138        | 2308            | 262        | 2305            | 209              | 2310            |
| B2               | 140        | 2328            | 267        | 2330            | 212              | 2329            |
| B3               | 143        | 2357            | 273        | 2360            | 217              | 2360            |
| B4               | 137        | 2298            | 259        | 2290            | 207              | 2298            |
| B5               | 139        | 2318            | 265        | 2320            | 210              | 2316            |
| B6               | 142        | 2348            | 269        | 2340            | 215              | 2347            |
| B7               | 144        | 2367            | 275        | 2370            | 219              | 2374            |

Fig. 4. HITRAN CH$_4$ spectra (grey) resampled to the spectral resolution of AVIRIS-NG (red), AVIRIS-CL (green) and IG (blue) sensors. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

Fig. 5. Location of main CH$_4$ features (a–e) in relation to spectral sampling and band positioning of SWIR airborne sensors. The wavelengths of absorption features indicated in the legend correspond to the high-resolution spectrum (grey). In the lower part of the plot, bars correspond to bands of each sensor between 2150 – 2450 nm. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).
4.2. Image processing

4.2.1. CH$_4$ index

Spectral indices consist of an empirical mapping approach based on the spectral variation of a target. The combination of two or more bands of interest (i.e. band ratios or mathematical expressions) allows the extraction of information from the scene, reducing the data and indicating the relative abundance of the target (Jackson, 1983; Verstraete and Pinty, 1996). A new CH$_4$ index (CH4I) based on the main features of the CH$_4$ signature between 2280–2390 nm was created here to map the CH$_4$ plume in the airborne images (Eq. (1)). The CH4I combines 7 bands from the CH$_4$ spectrum. The 4 bands in the denominator correspond to the deepest features in the signature of the gas between 2280–2390 nm (i.e. bands with lowest values), and the 3 bands in the nominator correspond to their shallower opposites (i.e. band with highest values). Using the CH4I the plume will be highlighted in brighter pixels in the output imagery.

A CH$_4$ signature compatible with the airborne sensor used is needed to extract the CH4I. Here, the bands from the equation were selected from the HITRAN CH$_4$ reference spectra and resampled to the spectral resolution and sampling interval of each imaging spectrometer (see Fig. S2 in the supplementary material). The wavelengths of B1–B7 used in the equation depend on the spectral sampling and should be adapted to the specific hyperspectral sensor used. To select the bands, the user must first identify the 4 deepest features between 2280–2390 nm (B4–B7). B1, B2 and B3 are the bands with higher values between bands B4–B5, B5–B6 and B6–B7, respectively. Fig. 3 illustrates an example of the bands selected as input in the CH4I. Table 2 present the bands used to

![Fig. 6. RGB composition (left), CH4I output (middle) and MTMF output (right) for (A) AVIRIS-NG data, (B) IG data and (C) AVIRIS-CL data. Red squares in the RGB images indicate the emission source. CH$_4$ plumes appear in white and purple in the CH4I and MTMF results, respectively. A Gaussian stretch was applied to the RGB images to improve the color contrast. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).](image-url)
feasibility (false positive). Therefore, a pixel properly classified must be formed without the necessity of knowing all endmembers in the scene. Pressing the response of the background, the classification can be performed by suppressing the noise in the detection of the CH$_4$ plume, white noise$^1$ was added to the HITRAN CH$_4$ spectrum after resampling to the hyperspectral IG sensor, AVIRIS-CL and AVIRIS-NG resolutions. The noise was added with the HypPy Tools (Bakker et al., 2014) using Eq. (2): \[ S_n = \left( S + N \ast \text{numpy.random.random}(\text{len}(S)) \right) - \frac{N}{2} \] were $S$ is the original signal (image or spectrum); $N$ is the percentage of noise added to the signal, and $\text{numpy.random.random}$ is the white noise (a signal with random variables that can assume a numeric value in the interval $\text{len}(S)$). The percentage of noise added to images and spectra varied from 1 to 15% (0.01 to 0.15).

Fig. 7 shows the SNR estimated from the images of each airborne sensor (i.e. SNR = mean/standard deviation of 500 pixels selected over a homogeneous bright area from each image. To evaluate possible interference related to noise in the detection of the CH$_4$ plume, white noise$^1$ was added to the HITRAN CH$_4$ spectrum after resampling to the hyperspectral IG sensor, AVIRIS-CL and AVIRIS-NG resolutions. The noise was added with the HypPy Tools (Bakker et al., 2014) using Eq. (2):

\[ S_n = \left( S + N \ast \text{numpy.random.random}(\text{len}(S)) \right) - \frac{N}{2} \] were $S$ is the original signal (image or spectrum); $N$ is the percentage of noise added to the signal, and $\text{numpy.random.random}$ is the white noise (a signal with random variables that can assume a numeric value in the interval $\text{len}(S)$). The percentage of noise added to images and spectra varied from 1 to 15% (0.01 to 0.15).

5. Results

5.1. Analysis of sensor design

The HITRAN spectrum resampled to AVIRIS-NG resolution contains two prominent features at 2290 and 2370 nm, which can be related to the HITRAN CH$_4$ absorption features at 2289 and 2370 nm (Fig. 4).

Differences in spectral sampling have a significant effect on resolving the CH$_4$ absorption feature (Fig. 5). The spectral sampling of the AVIRIS sensors is uniform along the spectra (CL: 10 nm and NG: 5 nm). Although the IG sensor has an average sampling of 6.3 nm in the SWIR, in the region where the CH$_4$ feature is located (2100–2500 nm), the spectral sampling is an average of 7 nm. This makes the center of the deepest HITRAN CH$_4$ features (“a” and “e” in Fig. 5) to fall on the edges of the IG sensor bands. For AVIRIS-NG, the bands are best positioned to capture the CH$_4$ features. In contrast, features “b”, “c” and “d” (Fig. 5) are better located in the AVIRIS-CL and IG sensors.

5.2. Image processing

The processing results for each image are displayed in Fig. 6. The plumes were highlighted in both AVIRIS images, with sizes of 1.6 km and 0.03 km, respectively. Positive results were not achieved with the processing of IG images. Controlled experiments (IG sensor and AVIRIS–NG images) were ground validated by field measurements of CH$_4$ sources with controlled gas rate emissions (Scafutto et al., 2018; Thorpe et al., 2016). The 2015 gas leakage from Aliso Canyon (AVIRIS–CL image) was quantified by Conley et al. (2016) and mapped by Thompson et al. (2016).

5.3. Noise simulation

Fig. 7 shows the SNR estimated from the images of each airborne sensor (i.e. SNR = mean/standard deviation of 500 pixels selected over a homogeneous bright area). The curves are similar in shape. However, the signal observed in the IG image (Fig. 7d) is noisier (i.e. higher variations of values along the wavelength range) than in both AVIRIS images (Fig. 7a and b). Due to the commonly high quality of IG data, we believe that this unexpected difference in shape and roughness in the SNR estimated from the IG imagery resulted from problems with the radiometric calibration of the sensor on the day of the experiment (20th August 2010). Comparing the SNR estimated from the same area of the image acquired on the 18th August 2010 (no CH$_4$ release this day), it can be seen that, with proper calibration, the estimated SNR resembles the SNR estimated from AVIRIS-NG (as expected due to the high resolution of both sensors).

Fig. 8 compares SNR estimated from the original images (referred to as REFERENCE in the plots), with SNR estimated from images after the addition of white noise. Since no CH$_4$ plume was mapped in the IG image, the AVIRIS-NG data were resampled to the IG sensor spectral.
resolution with a spectral response function (in which the noise was added subsequently), to simulate the effects of noise increase for this sensor. After the addition of white noise, the resulting images were processed with the CH₄ index. Results show that the number of pixels in the plumes gradually decreases with an increase in noise (Fig. 9). However, due to the higher density of the plume in the AVIRIS-CL image (caused by a higher gas rate), a superior percentage of noise (15%) was necessary to completely mask the signal of the gas, in comparison to AVIRIS-NG (7%) and the simulated IG (5%) images. Fig. 8 shows that the addition of peaks in the signal is the main cause for the reduction in image quality, instead of the decrease in the SNR value.

To assess the effect of noise in the CH₄ feature, the same function applied to the images (Eq. 2) was used to add white noise to the CH₄ spectrum resampled to the spectral sampling of each sensor (Fig. 10). For AVIRIS-NG, the deepest features of the gas turn into double features at 7% of noise (Fig. 8b). In the case of the IG sensor and AVIRIS-CL, the CH₄ spectrum is strongly modified after addition of 4–5% of noise.

6. Discussion

The airborne sensors analyzed in this study were not specifically designed for the detection of CH₄ plumes. However, the default spectral sampling of AVIRIS-CL and AVIRIS-NG, along with a high SNR and high spectral resolution, enables the use of both sensors for the task. Despite having a sufficiently high spectral sampling (~7 nm in the CH₄ region) and a SNR comparable to AVIRIS-NG, the IG sensor was not effective in the detection of CH₄ plumes. Results demonstrated that high resolution alone is not enough for CH₄ mapping. The wavelength position of CH₄ features in relation to the center of sensor bands, as well as sensor calibration, must be taken into consideration, as discussed in the following topics.

6.1. Feature position x bandwidth and spectral sampling

Our analysis showed that besides suffering from poor calibration, the position of the bands for the IG sensor is not ideal, making the strongest features of the gas to be sited at the edges instead of in the center of the bands. The slight increase in spectral sampling between 2100–2500 nm
(7 nm) yields a CH$_4$ signature that resembles more AVIRIS-CL spectra (10 nm sampling) than AVIRIS-NG spectra (5 nm sampling), in terms of shape and feature depth. This difference in spectral sampling may have enhanced the strong features located at 2290 nm and 2370 nm in the AVIRIS-NG data, which, besides facilitating the detection of the gas, also makes the images of this sensor less sensitive to noise. Furthermore, due to band positioning, both AVIRIS sensors are less sensitive to water vapour (H$_2$O), as observed in Fig. S1 (Supplementary Material). When resampling the high-resolution CH$_4$ and H$_2$O signatures to AVIRIS-NG and AVIRIS-CL spectral resolution, there is no feature overlap. However, when resampling to the IG sensor resolution, there is an overlap between CH$_4$ and H$_2$O features at 2354 nm, and also a shoulder of the H$_2$O feature at 2387 nm over the CH$_4$ feature located at 2374 nm.

6.2. Sensor calibration and noise

The addition of white noise to the CH$_4$ spectra (Fig. 10) shows that the narrower and deepest features seen in the AVIRIS-NG spectrum related to the gas are preserved even with higher levels of noise. In the case of AVIRIS-CL and the IG sensor, CH$_4$ features are similar in depth and width, which makes both more susceptible to misclassification as noise. This could be seen in the results stemmed from the IG sensor image processing, in which a poor radiometric calibration probably prevented the CH$_4$ plume to be mapped. Since CH$_4$ features are weak, the addition of noise can lead to misclassification or the removal of the features when noise reduction techniques are applied.

The addition of random noise to the airborne images (Fig. 9) and to the resampled HITRAN CH$_4$ spectra (Fig. 10) has shown that the number of peaks added to the curve (i.e. the abrupt variation of values along the wavelength) is the main change in the signal, rather than the decrease in the SNR value itself. Looking at the simulated images from AVIRIS-NG (Fig. 9a) and AVIRIS-NG resampled to the IG sensor resolution (Fig. 9b), it can be noticed that the CH$_4$ plume virtually disappears with additions of 7% and 5% of noise, respectively, which is consistent with the simulations done with the resampled HITRAN CH$_4$ spectra (Fig. 10). A comparison of the estimated SNR plots of these images (Fig. 8) shows that new peaks appear. In contrast, when looking at the SNR plot of the simulations from the original IG image (Fig. 8d), there is no major change with the addition of noise. It is possible to note a variation in the depth of the peaks, but the shape and number of peaks in the curve resemble the reference estimated SNR.

6.3. Plume density

On top of calibration problems and misplaced ideal band positioning to detect CH$_4$ features, the density of the plume may also have not been enough for its detection with the IG sensor in the SWIR range, even with the high flow rate of the experiment. Assuming that the plume has a low density, the background components in the scene could have hampered detection. The more transparent the plume, the higher the possibility of the CH$_4$ feature to be overlapped by background materials, especially the ones with spectral features in the same region (e.g. carbonates, petroleum products - Ayasse et al., 2018). In contrast, it was necessary to add a double amount of noise (15%) to the AVIRIS-CL image, in comparison to AVIRIS-NG (7%), to mask the signal of the plume. Results demonstrated that despite the changes in the estimated SNR with the increasing addition of noise, the significantly higher density of the plume strengthens the signal of the gas, facilitating the detection.

7. Conclusions

In this study, three operational airborne imaging spectrometers were evaluated for CH$_4$ plume mapping. In contrast to the scientific-grade AVIRIS-CL and AVIRIS-NG sensors, the industry-grade (IG) sensor
failed in detecting the CH₄ plume. It can be concluded that both the spectral sampling and radiometric calibration were critical for successfully mapping CH₄. Bands centers positioned in wavelengths nearest to the narrow CH₄ absorption features also contributes to better resolving the signature of the gas. Poor calibration of the IG sensor led to high variation in the SNR values estimated from this sensor. The addition of random noise to the signal proved to be one of the main causes for the decline of image quality, causing problems in detection of CH₄ in the simulation with all three sensors. Since CH₄ absorption features are shallow in the SWIR, they can overlap with noise spikes, masking the gas features. Future airborne imaging spectrometers with bands properly positioned in specific wavelengths, a fine spectral sampling and properly calibrated (i.e. uniform SNR) should be able to resolve narrow CH₄ features, possibly overcoming confusion with background materials.

CRediT authorship contribution statement

Rebecca Del’Papa Moreira Scafutto: Conceptualization, Methodology, Data curation, Validation, Writing - original draft, Writing - review & editing. Harald van derWerff: Validation, Writing - review & editing. Wim H. Bakker: Software, Writing - review & editing. Freek van derMeer: Supervision, Resources, Writing - review & editing. Carlos Roberto de Souza Filho: Conceptualization, Methodology, Supervision, Resources, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.jag.2020.102233.

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Fig. 10. Effect of noise increase on methane spectral signature. First spectrum (solid black line) in each plot correspond to the CH₄ high-resolution transmittance spectrum extracted from the HITRAN database, resampled to spectral resolutions (FWHM: full width at half maximum) of AVIRIS-CL (10 nm), IG (6.3 nm) and AVIRIS-NG (5 nm) sensors. Subsequent signatures correspond to simulations of [resampled CH₄ spectrum + (% white noise), as described in Eq. 2. Numbers above each spectrum indicate the percentage of noise added to the original CH₄ signature resampled to each sensor. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).
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