Challenges in Data Integration, Monitoring, and Exploration of Methane Emissions: The Role of Data Analysis and Visualization

Parisa Masnadi Khiabani* Gopichandh Danala† Wolfgang Jentner‡ David Ebert§

Data Institute for Societal Challenges
University of Oklahoma

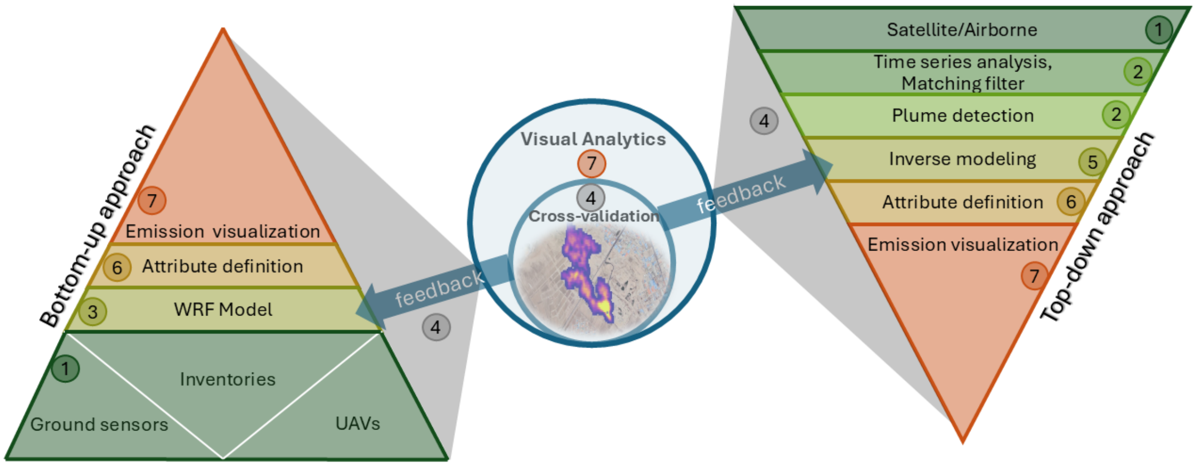

Figure 1: Heterogeneous data integration and visualization for bottom-up and top-down approaches to detect and localize methane emissions. The picture inside the cross-validation part is from [28]. Visual analytics can improve the results of any step. Both approaches have individual deficiencies that a visual analytics cross-validation approach can mitigate.

Abstract

Methane (CH_4) leakage monitoring is crucial for environmental protection and regulatory compliance, particularly in the oil and gas industries. Reducing CH_4 emissions helps advance green energy by converting it into a valuable energy source through innovative capture technologies. A real-time continuous monitoring system (CMS) is necessary to detect fugitive and intermittent emissions and provide actionable insights. Integrating spatiotemporal data from satellites, airborne sensors, and ground sensors with inventory data and the weather research and forecasting (WRF) model creates a comprehensive dataset, making CMS feasible but posing significant challenges. These challenges include data alignment and fusion, managing heterogeneity, handling missing values, ensuring resolution integrity, and maintaining geometric and radiometric accuracy. This study outlines the procedure for methane leakage detection, addressing challenges at each step and offering solutions through machine learning and data analysis. It further details how visual analytics can be implemented to improve the effectiveness of the various aspects of emission monitoring.

Index Terms: methane leakage, real-time monitoring, Spatiotemporal visualization techniques.

*e-mail: parisa.masnadi@ou.edu
†e-mail: danala@ou.edu
‡e-mail: wjentner@ou.edu
§e-mail: ebert@ou.edu

1 Introduction

Methane (CH_4), with a warming potential more than 28 times greater than carbon dioxide (CO_2) over a century, is crucially targeted in climate change mitigation efforts [33, 34, 43]. Emissions from natural gas systems, landfills, and livestock present substantial monitoring and mitigation challenges. Innovations in CH_4 capture technologies are transforming these emissions into clean energy. Regulatory policies, including carbon pricing and renewable energy incentives, alongside advanced monitoring technologies, emphasize the benefits of reducing CH_4 emissions and advancing green energy solutions.

A near real-time system is crucial for continuous monitoring (CMS) and fugitive detecting CH_4 emission detection. This system provides actionable insights for mitigation. Integrating spatiotemporal data from ground sensors, unmanned aerial vehicles (UAVs), aircraft, and satellites, improves detection capabilities, and mitigates the limitations of individual measurement tools [8, 17, 37]. However, analyzing this complex data requires powerful computational frameworks and data-driven models to enable effective analysis and mitigation [45]. The ideal framework should be scalable and flexible to adapt to new technologies and regulatory changes [2]. It should include robust verification and validation mechanisms to enhance data credibility, ensure active stakeholder engagement, enable stakeholder decision-making, and maintain cost-effectiveness.
Advanced visual analytics (VA) techniques can fully exploit the potential of these data. These techniques are vital for transforming raw data into practical decisions and for effectively communicating the findings to decision-makers [5, 10].

This paper, as illustrated in Fig.1, reviews the procedure for detecting CH_4 emissions, measuring their concentrations, and creating a visual analytics decision-making environment. It covers both top-down and bottom-up approaches and discusses their integration with the Weather Research and Forecasting (WRF) model [31]. The paper identifies challenges associated with each step and examines how data analysis and visualization techniques can address these issues, offering effective solutions.

2 Challenges and Opportunities using Visual Analytics

CH_4 emissions significantly contribute to global warming. To combat these emissions, enhanced regulatory measures [13, 24] such as the Environmental Protection Agency's (EPA) imposition of a waste emissions charge on facilities exceeding set emission thresholds are in place, with charges increasing annually from 2024 onwards [15]. Effective measurement and monitoring of emissions involves advanced sensing technologies including satellites, UAVs, ground sensors, and data from inventories like the National Ecological Observatory Network (NEON)

Effective data integration, visualization, and interactive analytical approaches are crucial for understanding various data streams and deriving actionable solutions for detecting and mitigating emissions. Applying advanced data analysis techniques and integrating data-driven models enhances the resolution of datasets with sparse or irregular sampling, identifies measurement errors, and improves the accuracy of volume and source location estimation. These visual analytic frameworks, combined with novel artificial intelligence (AI) and machine learning (ML) approaches that facilitate human-in-the-loop interactions, can significantly enhance efficacy and adaptability across different monitoring sectors. Data exploration techniques within the visual analytics system allow operators and users to explore various combinations of data fusion and assimilation, enabling the investigation and identification of optimal data fusion techniques to derive effective mitigation actions. This integration also allows for data comparison and cross-validation, helping identify inconsistencies and anomalies. These VA systems must be customized for different users (like O&G operators, regulators, federal agencies, communities,& tribal agencies, etc.) to provide appropriate information and monitoring capabilities required for those stakeholders.

2.1 Measurement Technologies and Challenges

As mentioned in the introduction, various tools and technologies are employed to measure methane emissions, each with unique capabilities and limitations. Satellite monitoring provides broad coverage, including remote areas, but suffers from lower resolution and can be affected by weather and timing, making it best for identifying large leakage emissions, which are a source of huge methane emissions, and are referred to as super emitters. Airborne methods offer more detailed local data but are expensive and also weather-dependent. UAVs and ground-based systems provide accurate, real-time data but need significant infrastructure for large-scale effectiveness [3, 51]. Inventory data, while not updated in real-time, is crucial for improving WRF model predictions and detailed bottom-up measurements.

The top-down approach to estimating CH_4 emissions uses atmospheric measurements from ground stations, aircraft, or satellites to assess regional or global emissions. This method combines these measurements with meteorological data and atmospheric chemistry models to calculate total emissions. However, it faces challenges due to its reliance on complex modeling, the accuracy of atmospheric models, and the density and distribution of measurement stations or remote sensing coverage.

The bottom-up approach provides a detailed analysis of CH_4 emissions by tracking their sources and quantities, though managing the complex data is challenging. Advanced visualization tools like Geographic Information Systems (GIS) are essential for transforming this data into actionable insights. For instance, a GIS-based method helps model and visualize energy usage and greenhouse gas (GHG) emissions, providing detailed insights into how behavioral and technical changes affect energy patterns and emission hotspots, which aids in developing effective energy policies [27]. Additionally, as noted in [35], addressing discrepancies in national inventories through a detailed CH_4 inventory enhances the accuracy of global warming and air quality models. Techniques like Sankey diagrams, referenced in [9], visualize emission flows across sectors, helping to identify crucial areas for targeted mitigation efforts. An example is the analysis of Canada's GHG emissions [9], which shows significant impacts, particularly from Alberta's oil and gas and Ontario's transportation sectors, pointing to areas where targeted actions could yield major benefits.

Satellite and airborne hyperspectral and multispectral imagery are used for visualizing CH_4 point sources. Matched filter techniques and adaptive coherence methods are applied to raw data to identify specific signatures associated with CH_4 , allowing for the visualization and quantification of discrete CH_4 plumes [43]. Detecting emissions smaller than a pixel using satellite data is particularly challenging. Controlled release experiments, where known quantities of CH_4 are emitted, have been used to validate emission quantification algorithms in satellite data, with airborne sensors measuring these controlled plumes [43]. This process is enhanced by sub-pixel resolution analysis, which aids in calibrating and validating satellite CH_4 products, thereby refining the accuracy of satellite sensors. Additionally, another challenge is the atmospheric effects on satellite observations. Atmospheric transport models [43] can be employed to simulate the dispersion of CH_4 plumes, which helps in calibration by understanding how atmospheric conditions affect satellite observations.

2.2 Emission Detection

Time series and anomaly detection algorithms are used to detect plumes in large satellite datasets, which can sometimes trigger false alarms. To address this, Ouerghi et al. [32] utilize the Reed-Xiaoli algorithm and adjust detection thresholds with a counteractive statistical model to reduce these false alarms. Further, in the "plume detection" part of Fig.1 [41], hyper/multi-spectral imaging provides a 3D view of the area across different wavelengths. This data is processed using a matched filter technique to enhance CH_4 detection, which involves refining the raw data to clarify the CH_4 spectral signature [41]. The refined data is then orthorectified to create a 4D CH_4 map. This map includes RGB layers and an additional layer that displays CH_4 concentrations in parts per million-meter (ppm-m) [26]. Human analysts must manually review these maps to accurately identify and delineate CH_4 plumes, separating them from non-plume artifacts. Visualization tools help enhance the display by providing more detailed information such as time and location through interactive features like pop-up menus [41]. These visualizations enable analysts to access additional contextual information, making the data more informative and easier to interpret.

2.3 WRF Model

WRF model, especially its Large Eddy Simulation (LES) version, plays a pivotal role in simulating critical atmospheric conditions like wind patterns and temperature profiles. The WRF-LES model, with its enhanced capability to simulate fine-scale atmospheric phenomena, significantly aids in accurately tracking plume movement

and predicting trajectories [23]. When integrated with satellite imagery, the WRF model's outputs, especially those about wind fields, enrich plume detection and analysis. This combination offers an in-depth view of meteorological factors over the study [31].
Visual analytics enable the use of different weather models, allowing for the comparison and testing of each model's efficiency across various regions.

2.4 Integration

Integrating and fusing multi-sensor data from terrestrial and drone-borne platforms is essential for achieving geometric and spectral accuracy but poses significant challenges. These challenges include the complex processing required for data alignment and fusion, environmental conditions affecting data consistency (enforce sensor recalibration), and the need for sophisticated software capabilities [25, 40]. Cross-validation techniques and advanced statistical reconciliation help enhance data accuracy [8], while data from various sources are consolidated into a centralized Data Warehouse [18].

Managing the heterogeneity, multidimensionality, and scalability of data, often containing semantic differences such as varied terminologies and units, further complicates data integration. To address these issues, methods like ontology-based integration, advanced data warehousing, and robust data mining and visualization are recommended [30]. Additionally, handling missing data entries due to incomplete metadata or equipment failures is crucial for maintaining data quality, with techniques such as hybrid clustering and hypergraph clustering being utilized to efficiently organize data into comparable groups [11].

The surge in data from devices and mobile cloud systems necessitates real-time processing for anomaly detection and security [21]. Newer frameworks like Hadoop, Spark, and Apache Storm enhance these capabilities [21]. Furthermore, combining satellite and airborne data with advanced image processing and atmospheric modeling enhances the detection and quantification of CH_4 emissions [16]. Despite these advancements, maintaining resolution integrity remains a challenge. Yokoya et al. [48] discuss various data fusion techniques such as component substitution, multiresolution analysis, spectral unmixing, and Bayesian. Among these, spectral unmixing proves particularly effective for CH_4 detection, while Bayesian probability is valuable for managing uncertainties and updating analyses with new data.

Merging raw hyperspectral data with geolocation information creates 3D hyperclouds, and significantly improves geological mapping and visualization. This requires meticulous geometric and radiometric corrections to ensure accurate real-world representation [40]. Finally, categorizing data based on resolution levels within databases helps manage multiple data representations effectively, ensuring efficient storage and retrieval for specific tasks [38].

2.5 Inverse Modeling

Quantifying CH_4 emissions accurately is challenging due to the spatial and temporal variability of sources. Inverse modeling addresses this by working backward from atmospheric methane measurements to identify emission sources and determine their rates and locations. This method uses data from satellite, airborne, or ground-based sensors combined with meteorological data to provide more reliable estimates than direct measurements, which may overlook intermittent or diffuse sources.

There are several methods to quantify emissions from observed plumes, including the Gaussian plume inversion method, source pixel method, cross-sectional flux method, and Integrated Mass Enhancement (IME) method [44]. While Gaussian plume modeling struggles with small, non-standard plumes due to turbulence, methods like IME and cross-sectional flux, which are less affected by turbulence, offer more accurate estimations by correlating total plume mass or measuring fluxes across plume transects to deduce source rates [12, 44].

2.6 Attribute Determination

The CH_4 monitoring system aims to quickly link detected methane plumes to their sources [12], crucial for monitoring global oil and gas resources. This requires an automated system for both detection and attribution. Techniques like OGNET [36] and METER-ML [52] employ deep neural networks to identify specific oil and gas sites, using models initially trained on datasets like ImageNet. However, remote sensing imagery often differs significantly in shape and channel number from ImageNet, affecting model performance. Studies have shown that models using the National Agriculture Imagery Program (NAIP) with its four spectral bands outperform others in automated detection of oil and gas infrastructures. This approach, while precise, depends on high-resolution data, limiting its accessibility and global coverage. Furthermore, despite advancements, manual review is still needed to reduce false positives and the approach struggles with smaller infrastructures like well pads and compressor stations. The need for more specialized detection methods and the effectiveness of various algorithms in this domain are areas requiring further research.

2.7 Visualization and Interactive Visual Analytics

CH_4 emissions are dynamic spatiotemporal data tracked through multiple sensors simultaneously. Visualizing these emissions is crucial for sense-making and getting a coherent picture of the emission and situation. VA is useful for estimating the severity of emissions, detecting polluted areas that may become hazardous, and detecting the root cause/source of the emission. In combination with simulations and ML, scenarios can be created to conduct "what-if" analysis useful for planning, maintenance, and regulation tasks.
Some previous work has focused on eliminating atmospheric interference as the key to enhancing visualization, and one effective method could be employing Principal Component Analysis (PCA), as discussed in Ouerghi et al. [32].
Another method for visualizing CH_4 emissions involves depicting the fluid dynamics of plumes, which can be achieved by condensing a series of images into a time map that illustrates the progression of the fluid [39]. Multivariate data can be displayed utilizing glyph maps to enhance the comprehension of complex spatiotemporal data [47]. The glyphs can display variations and trends, making them particularly useful for identifying and analyzing CH_4 emission patterns across various regions and times. Zhang et al. discuss using Kernel Density Estimation (KDE) and map visualization techniques, which are particularly effective for mapping CH_4 emission densities and identifying geographic and temporal patterns [49]. Visualizing emissions in atmospheric conditions is not only challenging due to largely interpolated weather data failing to detect local turbulences [20, 50], but also challenging for performance reasons of simulating and visualizing billions of particles [19, 29]. Interacting with such volumetric data increases the challenge as the user interface must stay reactive requiring performant calculation, simulation, and visualization techniques [14, 42].
Another method for displaying plume dispersion is through a space-time cube, where two dimensions represent space and the third time [1, 22]. While this allows understanding of temporal behavior better, losing the third spatial dimension might be inadequate for understanding atmospheric dispersions and turbu-

lence. On the other hand, having three spatial dimensions only allows having the time encoded in animating the data, such as a video, resulting in unwanted effects such as change blindness [7]. Technologies such as virtual reality and augmented reality may be effective, however, the large scale of emissions in nature might be challenging to convey whereas down scaling leads to oversight of important patterns. VA can be key in improving the accuracy of data fusion, science-based model integration (e.g., WRF-GHG), and eliminating errors and gaps in ground-based inventory measurements to help find and enable mitigation of fugitive CH_4 sources.
An interactive dashboard for GHG emissions visualization could significantly enhance the display and usability of plume data, offering a user-friendly tool for monitoring, analyzing, and reporting emissions on various scales. By benchmarking similar online dashboards, the fundamental requirements can be inferred, ensuring the creation of a robust and effective tool [4, 6, 46]. When zoomed out, this dashboard should integrate big circle symbols representing aggregate data from individual plumes, with size and color variations indicating total emission volume or concentration. Semantic zooming allows for detailed views of individual plumes at closer levels and aggregate views at broader levels, reducing clutter. Interactive elements would enable users to hover over plumes and circles to display key data like emission type, concentration levels, and detection time. A time slider or calendar feature would facilitate time series analysis, tracking changes over different periods. Data layer toggling, including wind patterns, temperature, or other environmental factors, would help correlate plume data with external conditions. Geographical context provided by map overlays showing urban areas, terrain, or weather systems would enhance understanding of plume locations. Customization options and filters would allow users to focus on specific aspects of interest, such as plume size or emission type. The dashboard should be responsive and accessible on various devices, ensuring a consistent experience across desktops, tablets, and mobile phones. Indicators of data sources and the accuracy or uncertainty level of displayed information would be essential, especially for synthesized or modeled data. Export and reporting tools would facilitate further analysis or sharing of visualizations.

To avoid clutter in visualizations, especially with infrastructure data, it is important to filter out or scale back certain elements when zooming out while emphasizing the exact locations of plumes and surrounding infrastructure in specific areas for better focus and understanding. This approach ensures that users can pinpoint relevant details without being overwhelmed by excessive information. These interactive tools can also establish a feedback loop incorporating user insights, model outputs, and visualization feedback, which is crucial for refining detection algorithms. Automated systems should be employed to flag potential discrepancies in the data, prompting human review and further adjustments. This iterative process ensures continuous improvement in methane emission detection and management systems.

3 Discussion

Due to their high global warming potential, CH_4 emissions from natural gas systems, landfills, and livestock pose significant environmental challenges. Capturing and reducing these emissions promptly is crucial for clean energy initiatives. Innovations in CH_4 sensing and monitoring technologies transform these emissions into valuable energy sources, mitigating environmental impacts and contributing to clean energy generation. However, capturing these emissions is challenging due to their diffuse and intermittent nature, requiring an integrated approach with data from ground sensors, UAVs, aircraft, and satellites. A near real-time CMS monitoring is essential for detecting and managing these emissions, providing actionable insights for mitigation. Such systems must facilitate capabilities for exploring different data integration combined with intelligent AI-assisted VA tools to enhance emission and anomaly detection. The main challenges could be summarized as follows:

- Appropriate recalibration of sensing technologies due to their variance from environmental impact.
- Data handling from different sources requires a firm and clear framework.
- Developing a multiscale spatiotemporal framework to support multi-level analysis and integrate the diversity of scales of input data.
- Continual refinement of modeling techniques that incorporate data-driven meteorology.
- Large clean and labeled datasets for training ML methods.
- Identifying appropriate data fusion techniques for diverse data sources.

Potential solutions include:

- VA that continually estimates and compensates for sensor inconsistencies due to environmental changes.
- ML addressing integration challenges, with imputation techniques fixing data inconsistencies.
- VA enhancing data interpretation, aiding in the integration of 3D atmospheric distribution with emission data for a deeper understanding, and enabling source identification and mitigation planning.
- New database development categorized by resolution can create multiple data representations for detected CH_4 emissions, enhancing localization, providing further information, and improving classification.

By addressing these challenges and leveraging advanced visualization and ML techniques, we can significantly improve the detection, management, and reduction of CH_4 emissions, contributing to a cleaner and more sustainable energy future.

4 Conclusion & Future work

In conclusion, developing a real-time VA monitoring system for GHG emissions, particularly CH_4 can enable the effective detection and mitigation of the complex and stochastic nature of these emissions. VA systems are enabling capabilities for building the necessary systems to accurately detect, locate, quantify, and mitigate known and fugitive emissions through a combination of sensing platforms, including advanced satellite imagery, atmospheric modeling, and computational techniques. This study highlights the critical need for these techniques, the challenges in integrating the detection techniques and modeling approaches, and producing detection and mitigation tools that can adapt to diverse and dynamic environmental conditions and evolving sensing modalities, ultimately contributing to more effective emission monitoring and mitigation efforts.
In the next step a dashboard will be created to enable integrated multidimensional real-time CH_4 monitoring. To achieve this, the system must address the challenges discussed and include necessary interactive tools. A system requirements assessment questionnaire has been developed and distributed to experts and stakeholders to understand their requirements. The survey findings will ensure the prospective system's effectiveness in providing stakeholders with capabilities to mitigate CH_4 emissions.

Acknowledgments

This research was supported by the Department of Energy (DOE) under Grant ID DE:FE0032292. The primary objective of the project is to rapidly and accurately assess chronic, episodic low-level, and super-emitting CH_4 emissions that are crucial for effective CH_4 emission mitigation.

References

[1] G. Andrienko, N. Andrienko, U. Demsar, D. Dransch, J. Dykes, S. I. Fabrikant, M. Jern, M.-J. Kraak, H. Schumann, and C. Tominski. Space, time and visual analytics. *International Journal of Geographical Information Science*, 24(10):1577–1600, Oct 2010. 3

[2] M. Appel and E. Pebesma. Spatiotemporal multi-resolution approximations for analyzing global environmental data. *Spatial Statistics*, 38:100465, Jul 2020. 1

[3] S. Asadzadeh, W. J. de Oliveira, and C. R. de Souza Filho. Uav-based remote sensing for the petroleum industry and environmental monitoring: State-of-the-art and perspectives. *Journal of Petroleum Science and Engineering*, 208:109633, Jan 2022. 2

[4] Carbon mapper data portal, 2024. Accessed: 2024-07-03. 4

[5] M. Chi, A. Plaza, J. A. Benediktsson, Z. Sun, J. Shen, and Y. Zhu. Big data for remote sensing: Challenges and opportunities. *Proceedings of the IEEE*, 104(11):2207–2219, Nov 2016. 1

[6] Climate trace data portal, 2024. Accessed: 2024-07-03. 4

[7] P. Cybulski and B. Medyńska-Gulij. Cartographic redundancy in reducing change blindness in detecting extreme values in spatio-temporal maps. *ISPRS International Journal of Geo-Information*, 7(1):8, Jan 2018. 4

[8] W. S. Daniels, J. L. Wang, A. P. Ravikumar, M. Harrison, S. A. Roman-White, F. C. George, and D. M. Hammerling. Toward multiscale measurement-informed methane inventories: Reconciling bottom-up site-level inventories with top-down measurements using continuous monitoring systems. *Environmental Science & Technology*, 57(32):11823–11833, Jul 2023. 1, 3

[9] M. Davis, M. Ahiduzzaman, and A. Kumar. How will canada's greenhouse gas emissions change by 2050? a disaggregated analysis of past and future greenhouse gas emissions using bottom-up energy modelling and sankey diagrams. *Applied energy*, 220:754–786, Jun 2018. 2

[10] T. De Groeve, A. Annunziato, Z. Kugler, and L. Vernaccini. Near real-time global disaster impact analysis. In *Information Systems for Emergency Management*, pp. 314–338. Routledge, 2014. 1

[11] V. M. Devagiri, P. Dagnely, V. Boeva, and E. Tsiporkova. Putting sense into incomplete heterogeneous data with hypergraph clustering analysis. In *International Symposium on Intelligent Data Analysis*, pp. 119–130. Springer, Apr 2024. 3

[12] R. M. Duren, A. K. Thorpe, K. T. Foster, T. Rafiq, F. M. Hopkins, V. Yadav, B. D. Bue, D. R. Thompson, S. Conley, N. K. Colombi, et al. California's methane super-emitters. *Nature*, 575(7781):180–184, Nov 2019. 3

[13] K. El Hachem and M. Kang. Reducing oil and gas well leakage: a review of leakage drivers, methane detection and repair options. *Environmental Research: Infrastructure and Sustainability*, 3(1):012002, Mar 2023. 2

[14] D. Engel, K. Greff, C. Garth, K. Bein, A. Wexler, B. Hamann, and H. Hagen. Visual steering and verification of mass spectrometry data factorization in air quality research. *IEEE transactions on visualization and computer graphics*, 18(12):2275–2284, Oct 2012. 3

[15] Environmental Protection Agency (EPA). Proposed rule by the environmental protection agency on methane emissions charges. https://www.regulations.gov/document/EPA-HQ-OAR-2023-0434-0001, 2024. Accessed: 2024-06-18. 2

[16] Á. E. Esparza, G. Rowan, A. Newhook, H. J. Deglint, B. Garrison, B. Orth-Lashley, M. Girard, and W. Shaw. Analysis of a tiered top-down approach using satellite and aircraft platforms to monitor oil and gas facilities in the permian basin. *Renewable and Sustainable Energy Reviews*, 178:113265, May 2023. 3

[17] T. A. Fox, T. E. Barchyn, D. Risk, A. P. Ravikumar, and C. H. Hugenholtz. A review of close-range and screening technologies for mitigating fugitive methane emissions in upstream oil and gas. *Environmental Research Letters*, 14(5):053002, Apr 2019. 1

[18] H. U. Gökçe and K. U. Gökçe. Multi dimensional energy monitoring, analysis and optimization system for energy efficient building operations. *Sustainable Cities and Society*, 10:161–173, Feb 2014. 3

[19] S. Grottel, M. Krone, C. Müller, G. Reina, and T. Ertl. Megamol—a prototyping framework for particle-based visualization. *IEEE transactions on visualization and computer graphics*, 21(2):201–214, Aug 2014. 3

[20] S. Grottel, G. Reina, J. Vrabec, and T. Ertl. Visual verification and analysis of cluster detection for molecular dynamics. *IEEE Transactions on Visualization and Computer Graphics*, 13(6):1624–1631, Nov 2007. 3

[21] R. A. A. Habeeb, F. Nasaruddin, A. Gani, I. A. T. Hashem, E. Ahmed, and M. Imran. Real-time big data processing for anomaly detection: A survey. *International Journal of Information Management*, 45:289–307, Apr 2019. 3

[22] N. R. Hedley, C. H. Drew, E. A. Arfin, and A. Lee. Hagerstrand revisited: Interactive space-time visualizations of complex spatial data. *INFORMATICA-LJUBLJANA-*, 23:155–168, 1999. 3

[23] X.-M. Hu. Real-time ch4 forecasting over the conus domain. https://caps.ou.edu/micronet/WRF_GHG_Forecasting.html, 2024. Accessed: 2024-08-13. 3

[24] R. B. Jackson, M. Saunois, P. Bousquet, J. G. Canadell, B. Poulter, A. R. Stavert, P. Bergamaschi, Y. Niwa, A. Segers, and A. Tsuruta. Increasing anthropogenic methane emissions arise equally from agricultural and fossil fuel sources. *Environmental Research Letters*, 15(7):071002, Jul 2020. 2

[25] M. Kirsch, S. Lorenz, R. Zimmermann, L. Tusa, R. Möckel, P. Hödl, R. Booysen, M. Khodadadzadeh, and R. Gloaguen. Integration of terrestrial and drone-borne hyperspectral and photogrammetric sensing methods for exploration mapping and mining monitoring. *Remote Sensing*, 10(9):1366, Aug 2018. 3

[26] S. Kumar, C. Torres, O. Ulutan, A. Ayasse, D. Roberts, and B. Manjunath. Deep remote sensing methods for methane detection in overhead hyperspectral imagery. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pp. 1776–1785, 2020. 2

[27] M. K. Mattinen, J. Heljo, J. Vihola, A. Kurvinen, S. Lehtoranta, and A. Nissinen. Modeling and visualization of residential sector energy consumption and greenhouse gas emissions. *Journal of cleaner production*, 81:70–80, Oct 2014. 2

[28] NASA/JPL-Caltech. Methane super-emitters mapped by nasa's new earth space mission, 2024. Accessed: 2024-08-13. 1

[29] T. Neuroth, M. Rieth, K. Aditya, M. Lee, J. H. Chen, and K.-L. Ma. Level set restricted voronoi tessellation for large scale spatial statistical analysis. *IEEE Transactions on Visualization and Computer Graphics*, 29(1):548–558, Sep 2022. 3

[30] S. L. Nimmagadda, H. V. Dreher, and A. Rudra. On a holistic modeling approach for managing carbon emission ecosystems. *Environmental Modeling & Assessment*, 21:763–801, Feb 2016. 3

[31] A. Nottrott, J. Kleissl, and R. Keeling. Modeling passive scalar dispersion in the atmospheric boundary layer with wrf large-eddy simulation. *Atmospheric environment*, 82:172–182, Jan 2014. 2, 3

[32] E. Ouerghi, T. Ehret, C. De Franchis, G. Facciolo, T. Lauvaux, E. Meinhardt, and J.-M. Morel. Detection of methane plumes in hyperspectral images from sentinel-5p by coupling anomaly detection and pattern recognition. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 3:81–87, 2021. 2, 3

[33] R. K. Pachauri, M. R. Allen, V. R. Barros, J. Broome, W. Cramer, R. Christ, J. A. Church, L. Clarke, Q. Dahe, P. Dasgupta, et al. *Climate change 2014: synthesis report. Contribution of Working Groups I, II and III to the fifth assessment report of the Intergovernmental Panel on Climate Change*. Ipcc, 2014. 1

[34] M. Saunois, A. R. Stavert, B. Poulter, P. Bousquet, J. G. Canadell, R. B. Jackson, P. A. Raymond, E. J. Dlugokencky, S. Houweling, P. K. Patra, et al. The global methane budget 2000–2017. *Earth System Science Data Discussions*, 2019:1–136, Jul 2019. 1

[35] S. Schwietzke, W. M. Griffin, H. S. Matthews, and L. M. Bruhwiler. Global bottom-up fossil fuel fugitive methane and ethane emissions inventory for atmospheric modeling. *ACS Sustainable Chemistry & Engineering*, 2(8):1992–2001, Jun 2014. 2

[36] H. Sheng, J. Irvin, S. Munukutla, S. Zhang, C. Cross, K. Story, R. Rustowicz, C. Elsworth, Z. Yang, M. Omara, et al. Ognet: Towards a global oil and gas infrastructure database using deep learning on remotely sensed imagery. *arXiv preprint arXiv:2011.07227*, 2020. 3

[37] A. Singh. Overview of emerging technologies for methane measure-

ment, monitoring and reduction in us onshore upstream oil & gas industry. In *Abu Dhabi International Petroleum Exhibition and Conference*, p. D011S029R006. SPE, Oct 2023. 1
[38] D. Skogan. Managing resolution in multi-resolution databases. In *ScanGIS*, pp. 99–113. Citeseer, 2001. 3
[39] A. Straub, N. Karadimitriou, G. Reina, S. Frey, H. Steeb, and T. Ertl. Visual analysis of displacement processes in porous media using spatio-temporal flow graphs. *IEEE Transactions on Visualization and Computer Graphics*, Oct 2023. 3
[40] S. T. Thiele, S. Lorenz, M. Kirsch, I. C. C. Acosta, L. Tusa, E. Herrmann, R. Möckel, and R. Gloaguen. Multi-scale, multi-sensor data integration for automated 3-d geological mapping. *Ore Geology Reviews*, 136:104252, Sep 2021. 3
[41] D. R. Thompson, A. Karpatne, I. Ebert-Uphoff, C. Frankenberg, A. K. Thorpe, B. D. Bue, and R. O. Green. Is-geo dataset jpl-ch4-detection-2017-v1. 0: A benchmark for methane source detection from imaging spectrometer data. *JPL Document D-101028*, Oct 2017. 2
[42] A. Tikhonova, C. D. Correa, and K.-L. Ma. Visualization by proxy: A novel framework for deferred interaction with volume data. *IEEE Transactions on Visualization and Computer Graphics*, 16(6):1551–1559, Oct 2010. 3
[43] D. M. Tratt, K. N. Buckland, J. L. Hall, P. D. Johnson, E. R. Keim, I. Leifer, K. Westberg, and S. J. Young. Airborne visualization and quantification of discrete methane sources in the environment. *Remote sensing of environment*, 154:74–88, Nov 2014. 1, 2
[44] D. J. Varon, D. J. Jacob, J. McKeever, D. Jervis, B. O. Durak, Y. Xia, and Y. Huang. Quantifying methane point sources from fine-scale satellite observations of atmospheric methane plumes. *Atmospheric Measurement Techniques*, 11(10):5673–5686, Oct 2018. 3
[45] J. L. Wang, W. S. Daniels, D. M. Hammerling, M. Harrison, K. Burmaster, F. C. George, and A. P. Ravikumar. Multiscale methane measurements at oil and gas facilities reveal necessary frameworks for improved emissions accounting. *Environmental science & technology*, 56(20):14743–14752, Oct 2022. 1
[46] Waste map earth data portal, 2024. Accessed: 2024-07-03. 4
[47] H. Wickham, H. Hofmann, C. Wickham, and D. Cook. Glyph-maps for visually exploring temporal patterns in climate data and models. *Environmetrics*, 23(5):382–393, Jul 2012. 3
[48] N. Yokoya, C. Grohnfeldt, and J. Chanussot. Hyperspectral and multispectral data fusion: A comparative review of the recent literature. *IEEE Geoscience and Remote Sensing Magazine*, 5(2):29–56, Jun 2017. 3
[49] Y. Zhang and W. Hong. Spatial-temporal evolution of carbon emissions and spatial-temporal heterogeneity of influencing factors in the bohai rim region, china. *Environmental Science and Pollution Research*, 2024:1–28, Jan 2024. 3
[50] Y. Zhang, H. Williams, F. Schreiber, and K. Klein. Visualising the Invisible: Exploring Approaches for Visual Analysis of Dynamic Airflow in Geographic Environments Using Sensor Data. In M. El-Assady and H.-J. Schulz, eds., *EuroVis Workshop on Visual Analytics (EuroVA)*. The Eurographics Association, 2024. doi: 10.2312/eurova.20241117 3
[51] B. Zhou, S. Zhang, R. Xue, J. Li, and S. Wang. A review of space-air-ground integrated remote sensing techniques for atmospheric monitoring. *Journal of Environmental Sciences*, 123:3–14, Jan 2023. 2
[52] B. Zhu, N. Lui, J. Irvin, J. Le, S. Tadwalkar, C. Wang, Z. Ouyang, F. Y. Liu, A. Y. Ng, and R. B. Jackson. Meter-ml: A multi-sensor earth observation benchmark for automated methane source mapping. *arXiv preprint arXiv:2207.11166*, 2022. 3