Introduction

CO_2 geological storage is universally recognized as an underpinning technology in advancing climate goals, facilitating industrial decarbonization, and enhancing net atmospheric CO_2 removal capabilities (Bui et al. 2018). Its large-scale implementation requires substantial evidence to demonstrate secure containment of significant CO_2 volumes across all stages of the CCUS (carbon capture, utilization, and storage) industrial chain, particularly under commercial-scale application.

Atmospheric CO_2 concentrations show complex variations from multiple sources (Friedlingstein et al. 2025). Under natural conditions, these fluctuations are governed by ecosystem carbon fluxes, regional topographic-climatic patterns, and extreme events (e.g., wildfires). From anthropogenic perspectives, industrial emissions, fossil fuel combustion, and potential CO_2 leakage from geological storage formation contribute to the complexities of concentration anomalies. Within this context, achieving CO_2 attribution monitoring bears critical significance: Technologically, this approach improves monitoring network design by identifying actual leakage signals, thereby avoiding unnecessary deployment of complex equipment and reducing monitoring costs. Socially, it enhances the credibility of environmental risk assessments, mitigates public concerns regarding eco-environmental security, and provides quantifiable evidence of irreversible leakage for carbon accounting.

This study aims to resolve the challenge of anomaly source identification in CO_2 geological storage monitoring. Through systematic literature review and data analysis, we comparatively analyze CO_2 attribution monitoring technologies and optimize monitoring reporting and verification (MRV) procedures.

Method and/or Theory

Peer-reviewed journals, books, technical reports (e.g. DOE/EPA/IPCC/IEAGHG), and EAGE/SPE/SEG publications were collected, and three key steps were taken to achieve the research objectives. First, we conduct systematic evaluations of CO_2 attribution monitoring technologies by analyzing their principles and methods. Second, we perform comparative assessments of their technical feasibility, costs, and field application results. Finally, an optimized MRV procedure is proposed.

Results

CO_2 attribution monitoring technologies can be classified into five major categories: eddy covariance, accumulation chamber monitoring, tracer-based techniques, process-based analysis, and deep learning algorithms (Fig. 1).

Eddy covariance primarily measures atmospheric CO_2 fluxes, while accumulation chambers monitoring focus on soil gas CO_2 fluxes. Both methods require comparison with background values to identify CO_2 anomalies.

Tracer-based techniques are further categorized into natural tracers and artificial tracers. Natural tracers primarily include radiogenic/stable isotopes (e.g., $\delta^{13}C$), noble gases (e.g., helium), hydrocarbons, and water chemistry indicators. Artificial tracers involve substances like sulfur hexafluoride (SF_6), chlorofluorocarbons (CFCs), perfluorocarbons (PFCs), halocarbons (HFCs), and esters. Tracers are non-reactive substances with low background concentrations in the environment. Their high sensitivity makes them effective tools for detecting, attributing, and quantifying potential CO_2 leakage.

Process-based analysis identifies anomalous CO_2 sources by analyzing gas-component correlation plots (e.g., O_2–CO_2, CO_2–N_2, CO_2–N_2/O_2 ratios). Deviations from established trendlines or baseline zones indicate potential leakage signals. This method eliminates the need for long-term background monitoring or complex statistical analyses, thereby offering greater operational flexibility and detection accuracy.

The deep learning algorithms detect anomalous CO_2 patterns trained on extensive background datasets. However, this technology currently has lower maturity compared to traditional methods.

Building upon conventional MRV frameworks, this study integrates attribution monitoring plan between base-case and contingency monitoring plans. This makes MRV more efficient and cost-effective by reducing unnecessary complex monitoring techniques when anomalies are detected (Fig. 2).

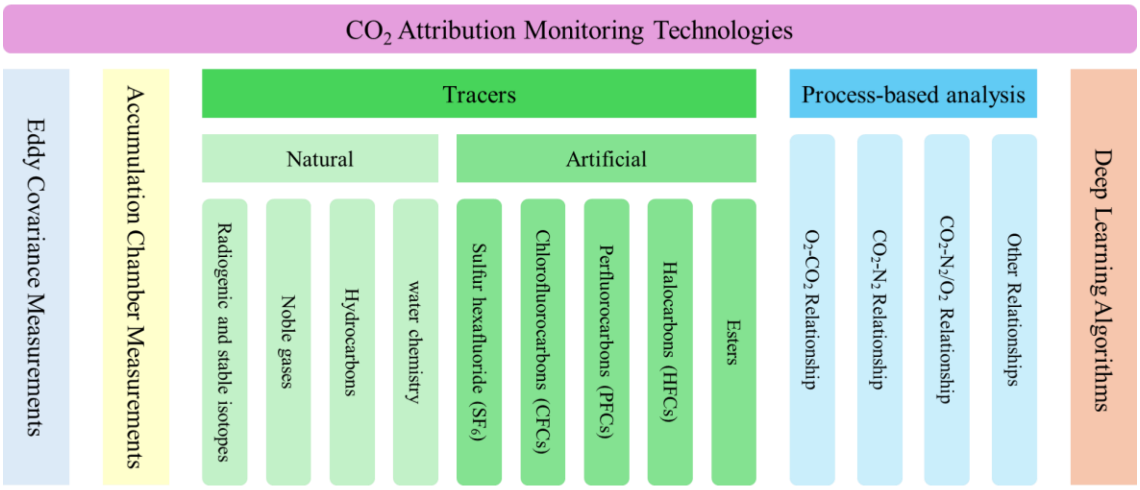

Fig. 1 CO_2 attribution monitoring technology system

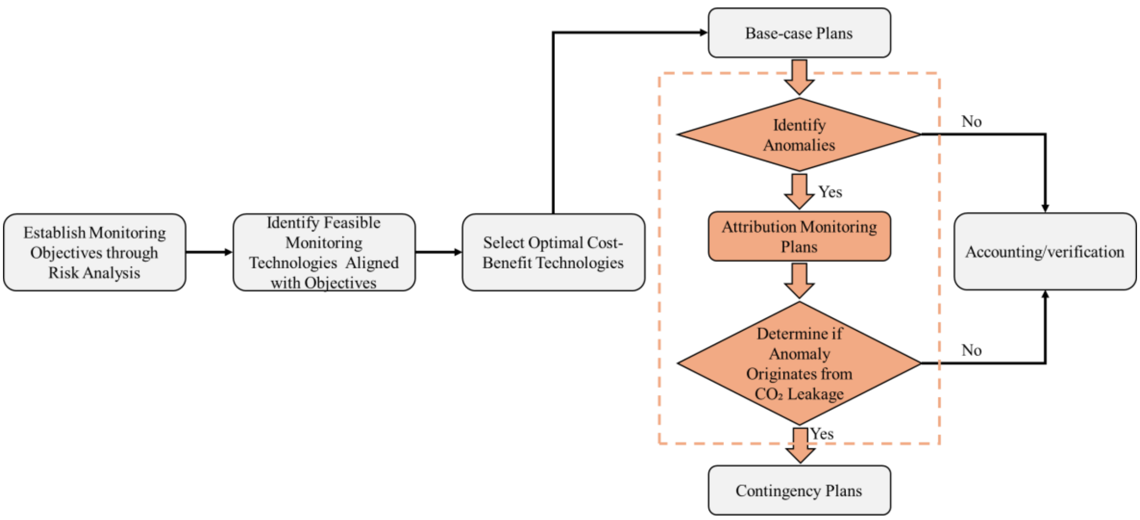

Fig. 2 MRV flow diagram considering CO_2 attribution monitoring

Conclusions

CO_2 attribution technologies can be classified into five major categories: eddy covariance, accumulation chamber monitoring, tracer-based techniques, process-based analysis, and deep learning algorithms. Eddy covariance, accumulation chamber monitoring, and deep learning techniques require extensive baseline data for comparison. Tracer-based techniques and process-based analysis demonstrate higher sensitivity and operational efficiency and therefore are recommended for prioritized application. Building upon conventional MRV frameworks, an optimized workflow is proposed by adding CO_2 attribution monitoring plan between base-case plan and contingency plan.

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References

Bui, M., Adjiman, C. S., Bardow, A., Anthony, E. J., Boston, A., Brown, S., Fennell, P. S., Fuss, S., Galindo, A., Hackett, L. A., Hallett, J. P., Herzog, H. J., Jackson, G., Kemper, J., Krevor, S., Maitland, G. C., Matuszewski, M., Metcalfe, I. S., Petit, C., Puxty, G., Reimer, J., Reiner, D. M., Rubin, E. S., Scott, S. A., Shah, N., Smit, B., Martin Trusler, J. P., Webley, P., Wilcox, J. and Mac Dowell, N. [2018] Carbon capture and storage (CCS): the way forward. *Energy & Environmental Science*, **11**(5), 1062–1176.

Friedlingstein, P., O'Sullivan, M., Jones, M. W., Andrew, R. M., Hauck, J., Landschützer, P., Le Quéré, C., Li, H., Luijkx, I. T., Olsen, A., Peters, G. P., Peters, W., Pongratz, J., Schwingshackl, C., Sitch, S., Canadell, J. G., Ciais, P., Jackson, R. B., Alin, S. R., Arneth, A., Arora, V., Bates, N. R., Becker, M., Bellouin, N., Berghoff, C. F., Bittig, H. C., Bopp, L., Cadule, P., Campbell, K., Chamberlain, M. A., Chandra, N., Chevallier, F., Chini, L. P., Colligan, T., Decayeux, J., Djeutchouang, L. M., Dou, X., Duran Rojas, C., Enyo, K., Evans, W., Fay, A. R., Feely, R. A., Ford, D. J., Foster, A., Gasser, T., Gehlen, M., Gkritzalis, T., Grassi, G., Gregor, L., Gruber, N., Gürses, Ö., Harris, I., Hefner, M., Heinke, J., Hurtt, G. C., Iida, Y., Ilyina, T., Jacobson, A. R., Jain, A. K., Jarníková, T., Jersild, A., Jiang, F., Jin, Z., Kato, E., Keeling, R. F., Klein Goldewijk, K., Knauer, J., Korsbakken, J. I., Lan, X., Lauvset, S. K., Lefèvre, N., Liu, Z., Liu, J., Ma, L., Maksyutov, S., Marland, G., Mayot, N., McGuire, P. C., Metzl, N., Monacci, N. M., Morgan, E. J., Nakaoka, S.-I., Neill, C., Niwa, Y., Nützel, T., Olivier, L., Ono, T., Palmer, P. I., Pierrot, D., Qin, Z., Resplandy, L., Roobaert, A., Rosan, T. M., Rödenbeck, C., Schwinger, J., Smallman, T. L., Smith, S. M., Sospedra-Alfonso, R., Steinhoff, T., Sun, Q., Sutton, A. J., Séférian, R., Takao, S., Tatebe, H., Tian, H., Tilbrook, B., Torres, O., Tourigny, E., Tsujino, H., Tubiello, F., van der Werf, G., Wanninkhof, R., Wang, X., Yang, D., Yang, X., Yu, Z., Yuan, W., Yue, X., Zaehle, S., Zeng, N., and Zeng, J.[2025] Global Carbon Budget 2024. *Earth Syst. Sci. Data*, **17**, 965–1039.