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Computational electromagnetic geophysics for groundwater system studies: A review of established practices and recent advances

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HIGHLIGHTS

- We review recent developments in electromagnetic methods applied in the context of hydrogeophysical studies.
- Time- and frequency-domain electromagnetic methods are examined with emphasis on computational methodologies and recent case applications.
- Significant advances have been made in electromagnetic modeling, but aligning these with groundwater modeling remains a complex task.
- Mutually informed workflows that build on high-performance computing could help to reduce uncertainties in groundwater models.

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ABSTRACT

Identifying effective solutions for locating groundwater resources and ensuring the quality of drinking water is increasingly urgent, given the challenges posed by climate change and population growth. This review investigates electromagnetic geophysical imaging techniques, in both time- and frequency-domain, that can provide valuable insights for groundwater assessment. We explore computational electromagnetic methods used to evaluate electromagnetic data and several recent hydrogeophysical case studies.

As open-source frameworks for modeling electromagnetic geophysical problems become available, a broader range of researchers can interpret their data with computationally advanced software. We provide an overview of documented open-source codes for evaluating electromagnetic data and analyze various hydrological targets in relation to their electromagnetic surveying technique and the computational method applied. Furthermore, we evaluate the potential of advanced computational techniques, including three-dimensional modeling, non-deterministic inversion and machine learning, to couple geophysical with numerical groundwater modeling and apply it in groundwater system studies. Despite obstacles such as complexity and resource demands, our findings indicate that the quantification and integration of predictive uncertainties from both electromagnetic and hydrological data and simulations would significantly improve the reliability of hydrogeophysical models. This can lead to a deeper understanding of groundwater systems and improved management practices.

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1. Introduction

This review reports on recent advances in electromagnetic (EM) geophysical methods focusing on computational developments and recently reported state-of-the-art applications to investigate groundwater systems. We consider time- and frequency-domain EM (TDEM and FDEM), while other methods such as induced polarization (IP), electrical resistivity tomography (ERT), and ground-penetrating radar (GPR) are beyond the scope of the paper. Our contribution mainly aims to examine recently published hydrogeophysical studies with respect to advances in computational methods. The term 'groundwater system' shall refer to any water system that can be found in the subsurface beneath the water table, from shallow permeable layers to deep aquifers.

Earth's groundwater is one of the most important resources that supports life and natural ecosystems (Poeter et al., 2020). However, freshwater extraction from the subsurface has to be conducted sustainably, without severely disturbing the hydrologic cycle by depleting or contaminating existing reservoirs. Effects of climate change intensify the frequency and severity of droughts, floods, and other hydrological extremes, leading to local insecurities in water availability and quality and a global depletion of long-term, non-renewable groundwater reservoirs, stressing the need for efficient groundwater characterization and monitoring techniques (Pörtner et al., 2022).

EM imaging methods are widely used to characterize electrical subsurface properties, which can be physically linked to hydrological parameters of interest, such as water salinity, rock porosity and permeability, lithology and the degree of water saturation. Being related to important hydraulic properties of aquifers needed to characterize groundwater dynamics (Slater, 2007), investigating the electrical properties of the subsurface facilitates the identification of groundwater reservoirs, the assessment of water quality for potential contamination, and the formulation of robust groundwater management strategies. The objective of near-surface EM studies extends beyond immediate water needs (McNeill, 1991; Butler, 2005), aiming to contribute to the development of resilient strategies for groundwater exploration and management.

Non-invasive geophysical methods became popular for environmental and engineering purposes when their cost-effectiveness for groundwater exploration was recognized. As a result, several review articles and book chapters (e.g., McNeill, 1990) dealing with the topic exist. A review published 30 years ago is specifically directed to integrated geophysical techniques applied for groundwater exploration (Goldman and Neubauer, 1994). It includes a classification of geoelectric and EM methods into controlled-source and uncontrolled-source methods, reviews the basic principles and describes the advantages and disadvantages of ERT, IP, TDEM, FDEM very low frequency resistivity (VLFR) and nuclear magnetic resonance (NMR) methods. Additionally, the authors report on four case histories of integrated groundwater surveys conducted between 1980 and 1993. Nobes (1996) and Tezkan (1999) emphasize the importance of electrical and EM methods for near-surface environmental applications by explaining the links between hydrogeological parameters and electrical properties, besides reviewing the methods concerning environmental studies. Pellerin (2002) elaborates on electrical and EM methods for environmental and geotechnical studies, including a section on aquifer mapping. Robinson et al. (2008) aim to develop a dialogue between the disciplines of Geophysics and Hydrology by elaborating on advances in geophysical instrumentation and their potential applicability for watershed-scale hydrology, identifying the use of airborne systems and integrated evaluation methods as particularly important. A comprehensive overview of groundwater geophysics is published in Kirsch (2009).

A more recent, insightful review paper by Binley et al. (2015) documents commonly used applied geophysical methods and relates geophysical properties to derived hydrogeological properties. Furthermore, the authors elaborate on the possibilities of geophysical applications to assess temporal changes in hydrological properties of the subsurface and to investigate biogeochemical processes and ecosystem dynamics. Among other future directions, they point out the idea of autonomous large-scale geophysical experiments, the importance of data fusion and the necessity of appropriate uncertainty estimation. McLachlan et al. (2017) and Alao and Abubakar (2025) give an overview of geophysical methods to characterize the groundwater–surface water interface. Specifically, the dual-coil system frequency-domain EM method and the airborne EM method are reviewed in Boaga (2017) and Auken et al. (2017), respectively. Recently published books (or chapters) about geophysical methods for environmental applications (Cassiani et al., 2020) and electrical imaging for hydrogeology (Singha et al., 2023) describe the geophysical methods but also include case studies, and build on the earlier book by Rubin and Hubbard (2006) which describes the fundamentals of geophysical methods and their application to hydrogeological studies.

We acknowledge that the aforementioned reviews and books provide valuable knowledge and insights about the growing field of hydrogeophysics. Here, we appraise the recently developed advanced computing methods for EM geophysics, including many open-source codes, and the possibility of generating ever-larger geophysical data sets as an optimal, yet computationally demanding combination for groundwater system investigations. Observing a lack of examination of the latest literature regarding this topic, we assembled the present review. The focus of this review paper lies on computational advancements over the past several decades to evaluate EM data (Section 2) and recent state-of-the-art applications for groundwater exploration and management purposes (Section 3). Section 4 evaluates the applicability of the different EM geophysical and computational methods to address practical groundwater-related questions and suggests improvements for the standard sequential workflow to couple numerical groundwater modeling with information obtained from EM data. For readers less familiar with EM geophysical methods, we have taken the liberty of including an appendix that seeks to briefly explain the EM methods relevant to this article.

2. Computational advancements in EM geophysics

The primary goal of geophysical imaging is to extract detailed information about the subsurface from indirect measurements. Achieving this requires solving an inverse problem, where the objective is to infer the distribution of subsurface properties along with estimates of uncertainty based on geophysical data (Tarantola, 2005). This task of finding a subsurface model that explains the measured data and, at the same time, represents the real subsurface properties is inherently complex. The non-uniqueness inherent to most geophysical inverse problems means that multiple solutions can satisfy measurements within errors, and requires regularization or other prior information to solve. To accurately predict the subsurface response to a given EM source, precise and reliable forward simulations are required (Zhdanov and Zhdanov, 2015). Modeling EM signals is complex; and while some simplifications are often made to make this more efficient (e.g., quasi-static or layered-earth approximations), there are significant opportunities to leverage modern computational methods and hardware to model EM systems more accurately.

Over the past two decades, improvements in numerical methods, parallel computing, software development, and hardware capabilities have significantly influenced EM geophysics, leading to progress in both forward and inverse modeling methodologies (Newman, 2014) through three-dimensional modeling, adaptive mesh design, constrained inversion, and machine learning (ML) algorithms. The motivation for applying such advanced simulation techniques is to improve our ability to model and image Earth's subsurface with greater accuracy and efficiency. EM imaging codes, which are intricate algorithms designed to address complex, parameter-dependent problems, have become increasingly sophisticated and capable (Werthmüller et al., 2021). Aarhus Geosoftware (Auken et al., 2015) is one of the commercial

Table 1
List of documented, open-source code projects for forward (FM) and inverse modeling (IM) of EM data; AEM: airborne EM, CSEM: controlled-source EM, FDEM: Frequency-domain EM, MT: Magnetotellurics (far-field approach), TDEM: time-domain EM. The list is not exhaustive; however, every effort has been made to locate relevant codes.

Mode	Name	Features	Language	Reference
1D FDEM	OCCAM1DCSEM	FM/Smooth IM (MT/CSEM)	Fortran, MATLAB	Key (2009)
	FEMIC	FM/IM (2D/3D constraints, dual-coil)	MATLAB	Elwaseif et al. (2017)
	FDEM1D	FM/Sensitivities (dual coil)	MATLAB, Python	Hanssens et al. (2019)
	FDEMtools3	FM/IM (dual-coil)	MATLAB	Deidda et al. (2020)
	EMagPy		Python	McLachlan et al. (2021)
	ES-RTD-FDEM	FM/IM (pseudo 2D/3D dual-coil)	MATLAB	Liu et al. (2023)
1D TDEM	TEM1D	FM/Sensitivities	Fortran	Christensen et al. (2026)
2D FDEM	OCCAM2DMT	FM/IM (MT)	Fortran, MATLAB	deGroot-Hedlin and Constable (1990)
	GoFEM	FM (MT and CSEM)	C++	Grayver and Kolev (2015)
	FEMT2D	FM (MT)	MATLAB	Börner (2020)
	MT2D		C++	Ren and Buntin (2023)
3D FDEM	ModEM	FM/IM (2D, 3D MT)	Fortran	Kelbert et al. (2014)
	FEMTIC	IM (MT)	C++	Usui (2015)
	PETGEM	FM (CSEM)	Python, C	Castillo-Reyes et al. (2018)
	GEMM3D	FM/Sensitivities (MT/CSEM)	Fortran	Nunes and Régis (2020)
	EM3DANI	FM (MT/CSEM)	Julia	Peng et al. (2021)
	elfe3D	FM (CSEM)	Fortran	Rulff et al. (2021)
	GEMMIE	FM/IM (MT)		Kruglyakov and Kuvshinov (2022)
	libEMMI	FM (CSEM)	C	Yang (2023)
	EMFEM	FM (FDEM)	C++	Qin et al. (2023)
	libEMMI_MGFD	FM/IM (CSEM)	C	Yang and Ping (2024)
	MTGeophysics.jl	FM (1D, 2D MT), IM (2D, 3D MT)	Julia	Mishra et al. (2026)
Multi-method	jif3d	Joint inversion	C++	Moorkamp et al. (2010)
	SimPEG	FM/IM (1D, 2D, 3D)	Python	Cockett et al. (2015); Heagy et al. (2017)
	PyGimli			Rücker et al. (2017)
	EEMverter			Fiandaca et al. (2023)
FDEM/TDEM	P223 suite	FM/IM (1D, 2D, 3D)	Fortran	Raiche et al. (2007)
	MARE2DEM	FM/IM (2D MT/CSEM)	Fortran, MATLAB	Key (2016); Haroon et al. (2018a)
	GA-AEM	FM/IM (1D TDEM, AEM)	C++	Brodie (2017)
	empymod	FM (3D layered, CSEM)	Python	Werthmüller (2017)
	emg3d	FM (CSEM)		Werthmüller et al. (2019)
	custEM	FM/IM (3D MT/CSEM)		Rochlitz et al. (2019)
	GeoBIPy	IM (1D, 2D, AEM)		Minsley et al. (2020)
	HiQGA	FM/IM (1D TDEM, FDEM, AEM, CSEM, MT	Julia	Ray and Myer (2019)
	WFTEM3D	FM (3D TDEM)	Fortran, MATLAB	Li and Cheng (2023)

computational frameworks frequently applied to evaluate EM data in order to image hydrological subsurface settings. In the following section, we will describe the recent computational advancements of forward and inverse modeling in EM geophysics. Many of the computational EM developments can be found in associated open-source codes (Table 1).

2.1. Forward modeling

Simulation of Earth's subsurface response to an EM source, also known as forward modeling in EM geophysics, has undergone significant evolution. Initially, semi-analytical solutions derived from Maxwell's equations were used, primarily focusing on 1D subsurface models and the frequency domain (Constable and Weiss, 2006). A 1D subsurface only varies along the vertical or depth direction, and thus only models horizontally layered conductivity structures. The 1D forward model, however, is *semi*-analytical, as it does not appear in closed form: it is a recursive relation with integrations over Bessel functions, requiring numerical methods. To simplify the related computations, a linear Low Induction Numbers (LIN) approximation was developed (Wait, 1962; McNeill, 1980), which is valid for sufficiently low frequencies and conductivities. Today, many near-surface FDEM instruments that provide readings in apparent conductivity still rely on this approximation. It is therefore necessary to post-process those readings, e.g., following the procedure in McNeill (1986). While these early methods were computationally efficient for simple models, they were insufficient for accurately representing complex and heterogeneous subsurface scenarios.

To address the limitations of semi-analytical methods in EM forward modeling, various numerical techniques have been developed over the years, evolving to tackle increasingly complex, multidimensional models in the time- and frequency domain. These techniques can be broadly classified into four main categories: finite differences (FD; (e.g., Mackie et al., 1994; Newman and Alumbaugh, 2002; Davydycheva et al., 2003)), finite volumes (FV; (e.g., Hermeline, 2009; Jahandari and Farquharson, 2014; Heagy et al., 2017)), finite elements (FE; (e.g., Jin, 2015; Um et al., 2013; Key and Ovall, 2011)), and integral equations (IE; (e.g., Raiche, 1974; Wannamaker et al., 1984; Wannamaker, 1991; Xiong and Tripp, 1997)). For a comprehensive review of the evolution and advancements in numerical methods within EM modeling, see Avdeev et al. (2002), Avdeev (2005), Börner (2010), and Pankratov and Kuvshinov (2016).

Hybrid modeling techniques that combine analytical and numerical methods have also gained traction. Notably, the Born Approximation (Li et al., 2010), initially used to linearize the forward problem, has been revisited and enhanced with modern computational techniques to address more complex subsurface scenarios. Guillemoteau and Tronicke (2016) explored a rapid hybrid spectral-spatial domain 3D forward modeling approach based on the Born approximation for loop-loop EM induction quadrature data in a low-induction number context. Although this approach may slightly underestimate the conductivity of highly conductive targets, it excels in speed and can mostly accurately reproduce structural information. Another recent hybrid approach, applied to TDEM, is proposed by Deleersnyder and Slob (2025), who combine a 1D analytical forward model with coarse numerical meshes to approximate the modeling error introduced by the standard 1D assumption. By exploiting the fact that the difference between 1D and 3D responses is well captured on a coarser mesh, the approach avoids full high-fidelity 3D simulations while still accounting for multidimensional effects. The computational speedup can be balanced with the required accuracy by finetuning the coarseness of the numerical mesh.

Improved numerical techniques have led to the development of new strategies to balance solution accuracy while managing computational costs in 2D and 3D numerical modeling. Unstructured grids are becoming more common to simulate complex subsurface settings including topography and detailed geological features (e.g., Key, 2016; Rochlitz et al., 2019; Castillo-Reyes et al., 2018; Rulff et al., 2021; Singh et al., 2020) where regular Cartesian grids are inefficient. Challenges associated with meshing 3D domains with unstructured grids can be overcome with meshing tools such as Gmsh, MeshLab, Tetgen or FacetModeller (Geuzaine and Remacle, 2009; Cignoni et al., 2008; Si, 2015; Lelièvre et al., 2018). Semi-unstructured meshes, like octree grids (Haber and Heldmann, 2007; Xiao et al., 2022b) offer some flexibility by allowing localized refinement, although they still face limitations due to their regular grid structure.

Adaptive mesh refinement techniques have been applied to focus computational resources on areas of interest (e.g., receiver locations, regions with strong conductivity contrasts or anomalies) while coarsening the mesh in less critical areas (Ren et al., 2013; Grayver and Kolev, 2015; Zhang, 2018; Rulff et al., 2021; Castillo-Reyes et al., 2023b; Spitzer, 2023). This results in faster simulations without sacrificing accuracy in key areas. High-order elements, explored for EM simulations in Schwarzbach et al. (2011); Grayver and Kolev (2015); Castillo-Reyes et al. (2018); Rochlitz et al. (2019); Weiss et al. (2023); Zhou et al. (2022), increase the order of interpolation functions to improve the solution accuracy without adding more elements to the model domain. Highly-parallelised, direct sparse matrix solvers, such as MUMPS (Amestoy et al., 2001) and PARDISO (Alappat et al., 2020), are often used for solving the large systems of equations encountered in 3D EM simulations. Additionally, multigrid methods (e.g., Mulder, 2006; Werthmüller et al., 2019) and the application of iterative solvers (e.g., Grayver and Kolev, 2015; Weiss et al., 2023) offer techniques to accelerate computations.

Developments in HPC such as parallel processing and Graphics Processing Units (GPUs) have notably reduced computation times, turning what was once a prohibitively lengthy process into a feasible one (Sommer et al., 2013; Tu et al., 2024; Dong et al., 2024). Available server farms enable cloud computations that allow modellers who lack in-house access to computer clusters to run large-scale simulations (Newman, 2014). These technological enhancements have particularly benefited FD and FE methods, allowing them to handle large-scale 3D modeling with greater efficiency and precision.

Machine learning and neural networks (NN) have started to significantly impact the field of EM simulations. For instance, Moghadas et al. (2020) demonstrated the effectiveness of neural network-based forward solvers for soil electrical conductivity imaging, which has proven valuable for large-scale Bayesian EM inversion. Moreover, Li et al. (2026) developed a 3D transient electromagnetic forward simulation code using deep learning frameworks. By employing artificial intelligence (AI)-driven techniques, this approach has enabled rapid and accurate predictions in resource exploration and environmental monitoring. ML techniques, including deep learning, are now used to develop fast surrogate models that approximate traditional numerical simulations. Trained on extensive datasets from simulations, these models can predict subsurface responses to EM sources with high accuracy and in a fraction of the time. This capability facilitates real-time or near-real-time forward modeling, which is crucial for applications requiring swift decision-making (Moghadas et al., 2020; Li et al., 2026).

ML is most frequently used for 1D forward modeling, where training with (faster) analytical models poses no constraints on the available training data. Bording et al. (2021) use a conventional NN for ground-based TDEM data and claim a factor 13 speed up compared to the accurate 1D forward models with 98% accuracy within the 3% relative error limit. For airborne EM (AEM) modeling, Asif et al. (2022b) train a NN for 1D forward modeling, including the flight altitude as an additional parameter, which adds complexity to the learning problem. Additionally, two separate NNs were trained, one to predict the forward response and one for the partial derivatives. A speed-up by a factor of 50 is claimed. Wu et al. (2023) have trained an alternative NN with a long short-term memory (LSTM) architecture with similar 'functionalities' and claim a factor 2700 speed-up. The step toward 3D modeling has already been made for frequency domain magnetotellurics (Conway et al., 2019; Peng et al., 2023), which suffer less from the computational burden of generating enough training data. For 3D TDEM-data, the main bottleneck is the computational burden related to the 3D simulations (e.g., Deleersnyder et al., 2024).

2.2. Inverse modeling

Inverse modeling is the process of reconstructing subsurface properties from observed EM data, ideally along with measures of parameter uncertainty (Tarantola, 2005). The solution to an EM inverse problem is not unique and is highly sensitive to noise in the data, presenting substantial computational challenges. To mitigate the non-uniqueness problem, regularization is applied, imposing smoothness or other constraints on the solution (Tarantola, 2005). These constraints ensure that the estimated model is geologically realistic when prior geological information is used in the regularization process. Significant advancements in computational methods over the past decades have greatly improved the efficiency of inverse modeling.

Geophysical models can be classified as 1D, 2D, 3D, pseudo-2D/3D, and 4D (timelapse/monitoring). Some authors use the term "3D inversion" to describe the process of obtaining a 3D inversion model, even when they actually use a 1D forward model. Traditional inversions were mainly 1D or 2D, but recent advancements have led to the development of comprehensive 3D inversion algorithms. This transition enables more adequate imaging of subsurface conductivity structures in complex geological environments. The integration of advanced numerical methods and HPC has made large-scale 3D inversion practical, especially in the frequency domain. In large-scale contexts where 1D forward modeling can be justified in most areas or access to HPC infrastructure is limited, an appraisal method can be used to identify subsets in which 3D forward modeling should be applied instead of the entire dataset (Deleersnyder et al., 2022).

Traditional deterministic inverse modeling approaches rely on non-linear optimization techniques to minimize the discrepancy between observed and predicted data. These methods are time-and memory-expensive as they are required to solve large non-linear systems iteratively (Haber et al., 2004) and require careful regularization to stabilize the inversion (Zhdanov, 2009). Gradient-based and adjoint (Egbert and Kelbert, 2012; Snyman and Wilke, 2018) optimization methods can be employed to compute the sensitivities required for parameter updates more efficiently. Deterministic inversion approaches are limited as they do not account for the non-uniqueness of the EM inverse problem, i.e., offer only a single model output, and often do not provide uncertainty and resolution estimates that are computationally expensive to obtain (Ren et al., 2013).

Probabilistic inversion, e.g., Bayesian approaches (Idier, 2013) or Kalman ensemble generators (Bobe et al., 2020), has gained attention to solve EM inversion problems. These techniques allow for the estimation of an ensemble of plausible subsurface resistivity models and provide a framework to incorporate prior information and quantify uncertainty in the inversion results (Gunning et al., 2010). Uncertainty quantification (UQ) helps to assess the reliability of the solution, which is especially important in the context of noisy or incomplete data. UQ is also possible with stochastic inversion methods such as Markov Chain Monte Carlo (Minsley et al., 2020; Ray and Key, 2012; Blatter et al., 2019) or other posterior sampling algorithms. Hansen (2021) use probabilistic approaches to explore the posterior distribution of models which have been applied to several EM problems. The obtained uncertainties of resistivity models can be directly propagated into hydrological modeling (Hauser et al., 2018; Christensen et al., 2017).

Advances in constrained and joint inversion methods have allowed the combination of different geophysical datasets (e.g., EM, seismic, gravity) to obtain models that better reflect the subsurface than the inversion of single data types (Moorkamp, 2017). This can be especially valuable for imaging complex geological settings where single data types might not be able to resolve all subsurface features.

Deep learning (DL) inversion methods have become increasingly versatile due to their standardized framework, which encompasses three key stages: data generation, model training, and model prediction. This framework enables DL techniques to be applied flexibly to various types of EM data. The underlying technique of DL, neural networks, can directly map EM data to subsurface property distributions (Noh et al., 2020; Feng et al., 2020; Bai et al., 2020; Li et al., 2020; Puzyrev and Swidinsky, 2021; Laloy et al., 2021), providing a promising alternative to traditional inversion methods. Moreover, ML techniques have been applied to improve traditional inversion schemes, using a supervised descent (Rao et al., 2025). Avoiding the time-consuming optimization step of the inverse problem, these data-driven approaches solve inverse problems more rapidly and with less reliance on initial model assumptions. However, their effectiveness depends on the quality and diversity of the training data and the model's ability to generalize across different scenarios (Moghadas et al., 2020). By using physics-based NNs (Wu et al., 2024) or training a separate forward/surrogate model (Deleersnyder et al., 2024), the user can control the inversion more traditionally: the type of regularization and the regularization parameter(s) can be easily modified and noise can be accounted for.

Recent work by Wu et al. (2022) highlights several factors influencing DL inversion outcomes, including dimensionality, noise levels, sample richness, and prior information. These factors are critical across all DL inversion methods. Compared to traditional inversion approaches, DL-based inversion routines require, after model training, significantly less computational effort (Puzyrev, 2019). They support near-real-time reconstruction of subsurface resistivity distributions while ensuring high numerical accuracy (Bai et al., 2020; Puzyrev and Swidinsky, 2021). Additionally, real-time DL inversion techniques offer the potential for conducting statistical or probabilistic inversion processes (Alyaev et al., 2021), which enhance the practicality of data-driven forward modeling in various applications (Rammay et al., 2022). Moreover, DL inversion methods are increasingly applied in geophysical monitoring, a challenging task essential for reservoir characterization studies (Colombo et al., 2020).

These advances in computational EM modeling not only improve the accuracy and efficiency of forward simulations, but also provide the foundation for emerging approaches that explicitly integrate EM data with hydrogeological modeling. This connection is further explored in Section 2.5, where recent developments in ML and probabilistic inversion are discussed in the context of groundwater applications.

2.3. Common modeling practices

Dual-coil EM

The dual-coil FDEM-method is applied for shallow investigations and has wide applications, including environmental monitoring, agriculture, archaeology, and groundwater studies. The detectability of an electrical contrast in dual-coil FDEM surveys depends on several factors, including the sensitivity of the instrument, the depth of the target, the strength of the contrast (i.e., the difference in electrical properties between two subsurface materials), the coil geometry, and the frequency used in the survey. In practice, a conductivity contrast of 10% between the target and the surrounding material is usually required for detection (Everett, 2012). However, larger contrasts are much easier to detect and are more commonly associated with clearer anomalies, especially at lower resistivity. For this reason, this method is commonly applied for mapping lateral apparent conductivity contrasts in order to detect targets, such as contaminants, salinity changes, and clay layers, among others (Butler, 2005). There are a few challenges to overcome when applying the dual-coil FDEM method. The first challenge is related to the noise in the measurements due to environmental factors. This may affect the data quality and thus the accuracy of the estimations. After data acquisition, filtering noise and removing data spikes caused by metallic objects or surface interference is necessary. A second challenge lies in obtaining a sufficient signal-to-noise ratio since the primary magnetic field (that of the transmitter dipole) is constantly present, while the secondary magnetic field (that of the induced currents in the subsurface) is significantly smaller (10^3 to 10^6 times smaller). Through the use of a bucking coil, the primary magnetic field is cancelled in the receiver, which requires excellent instrument calibration (Won et al., 2003). Third, FDEM systems are prone to drift as a result of temperature changes in the instrument over time, which require additional data processing steps (Delefortrie et al., 2014).

Off-time TDEM-systems do not need active bucking, as the primary magnetic field is switched off and thus no longer present in the receiver coil. However, the switch-off is never instantaneous; therefore, early measurements are lost which are most sensitive to the very shallow subsurface and careful instrument design is required to ensure that residual primary currents do not contaminate measurements. Therefore, TDEM-systems are generally used for deeper investigations (5 + meters), though some airborne TDEM systems make use of a bucking loop to remove the effects of residual primary fields at the receiver coil. The data processing is slightly more complicated than for FDEM due to the extra Fourier transform needed for the forward modeling.

When modeling the subsurface for dual-coil EM applications, a layered half-space is commonly assumed (Fig. 1). The computation for 1D layered media is easily performed and useful for inversion and mapping layered media. This method is suitable in cases of expected minimal lateral variation in subsurface resistivities. However, even layered-media inversion has non-unique solutions (Jackson, 1972). Carrizo Mascarell et al. (2024) demonstrate this limitation for 1D inversion of 3-layer earth models when using a common dual-coil FDEM instrument configuration.

Pseudo-2D/3D inversion methodology, also sometimes called Laterally Constrained Inversion (LCI), is commonly applied based on the knowledge of low spatial variation in the geology. This method leverages

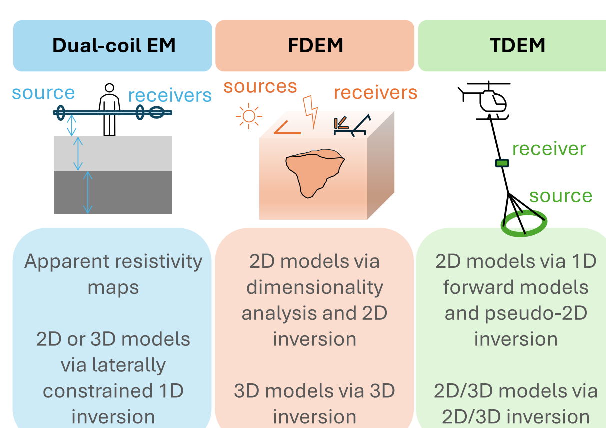

Fig. 1. EM methods, sketches of typical survey setups and commonly used modeling techniques; FDEM: Frequency-domain EM, TDEM: time-domain EM.

efficient 1D forward modeling but also imposes spatial constraints between neighbouring model locations (Auken et al., 2005). LCI is useful in situations where the individual inversion of data points might produce noisy or geologically unrealistic results due to non-uniqueness and data uncertainty.

Many examples of pseudo-2D/3D inversion applications exist: The method proposed by Triantafilis and Monteiro Santos (2013) is widely used for soil and groundwater studies (Davies et al., 2014; Huang et al., 2016, 2017), which is implemented in the *EM4Soil* software package (EMTOMO, 2013). Subsurface resistivity models are obtained through LCI where the modeling is based on the low induction number approximation (McNeill, 1980). LCI inversion has also been applied using Maxwell-based 1D forward modeling (Klose et al., 2022; Monteiro Santos, 2004; Carrizo Mascarell et al., 2026). McLachlan et al. (2021) present an open-source Python package to perform 1D forward modeling and LCI using deterministic or probabilistic methods (*EMagPy*). It applies Maxwell-based or low induction number forward modeling. Elwaseif et al. (2017) published a MATLAB package (*FEMIC*) to obtain 2D and 3D estimations of the subsurface resistivity through pseudo-2D/3D inversion, where a one-dimensional forward model is used, but lateral regularization constraints can be applied in 2D or 3D. Other implementations are demonstrated in Buccini and de Alba (2021); Klose et al. (2022, 2023). Deidda et al. (2020) present a method for 1D inversion with the MATLAB package *FDEMtools* using a regularized Gauss-Newton method. Liu et al. (2023) propose a method for pseudo-3D inversion using randomized tensor decomposition to reduce the model parameters and consequently the computational cost.

2D and 3D inversion of dual-coil EM measurements is not as common due to being computationally intensive and often not required, as dual-coil instruments are mostly sensitive to a small induction volume where the subsurface can be approximated as 1D (Yin et al., 2014; Reid et al., 2006).

General EM

Distant sources transmitting in the Hz and kHz ranges, as utilized in (radio)magnetotellurics and (CS)EM, have large induction volumes and, therefore, are sensitive to vertical and lateral resistivity variations in the subsurface. A thorough dimensionality analysis (e.g., Martí et al., 2009) can identify the suitability of a quicker 2D evaluation or the need for more expensive 3D inversion (Fig. 1). The significance of full 3D inversion is widely discussed, as inverting data with 3D signatures in lower-dimensional approaches can lead to substantial model artefacts (Liu et al., 2019; Macnae et al., 2012). Notable advancements in general FDEM codes have been made during the past two decades, particularly with respect to 3D evaluation (Oldenburg et al., 2020).

In the 2D and 3D domains, unstructured meshes to discretise the computational domain have become increasingly popular, especially since the Mare2DEM (Key, 2016) code became available. Additionally, constrained inversion, often leveraging seismic constraints to adjust smoothing across layer boundaries, is both feasible and commonly applied (e.g., with the EMILIA code: Yan et al., 2017; Vizheh et al., 2020). Several 3D codes for forward and inverse modeling, including proprietary options (e.g., Moorkamp et al., 2011; Grayver and Kolev, 2015; Usui, 2015; Smirnova et al., 2022) are now available and many are open-source (see Table 1). Manageable run times are achieved through efficient parallelization to facilitate cluster computations. Domain-decomposition approaches (Wang et al., 2007; Sheng et al., 2023) or sequenced workflows (Lindsey and Newman, 2015) can help manage large computational tasks. The ModEM software (Kelbert et al., 2014) is widely utilized for 3D inversion of EM data originating from sources in the far-field. In addition, 3D MT codes from Siripunvaraporn et al. (2005); Moorkamp et al. (2011); Grayver and Kolev (2015); Usui (2015) are frequently applied in the academic community. For CSEM inversion, 3D open-source frameworks such as e.g., custEM, in combination with pyGIMLi, and SimPEG (see Table 1) are becoming popular.

Depending on the system used and the associated induction volume, TDEM data are often evaluated in 1D (Piatti et al., 2010; Widodo, 2023) or 2D (e.g., Haroon et al., 2016). Deleersnyder et al. (2023) demonstrate airborne time-domain inversion utilizing a 1D forward model alongside pseudo-2D inversion. Instead of imposing a smoothness constraint, this approach employs wavelet theory to decompose the inversion model into the wavelet domain. By selecting a wavelet basis function with suitable characteristics, particularly in terms of sharpness, the desired minimum structure on the inversion model can be imposed. When the specific type of structure is unknown, these flexible methods allow for the generation of an ensemble of inversion models. Each model presents different features while still fitting the data, providing insights into the non-uniqueness of the inverse problem without the need for computationally expensive uncertainty quantification. Wavelet-based methods prove to be particularly effective for imaging sharp anomalies within globally smooth backgrounds (Nittinger and Becken, 2016; Deleersnyder et al., 2021).

3D time-domain computations are more demanding, but feasible (e.g., Haber et al., 2002; Xiao et al., 2022b, 2023; Liu et al., 2024; Shu et al., 2024). Advancements in modeling include more advanced time-stepping algorithms, for example by using implicit-explicit schemes. These methods allow larger time steps without losing accuracy, especially in regions with rapid conductivity changes. Fast Fourier Transform techniques have been integrated into TDEM processing for more efficient conversions between time and frequency domains. This helps speed up the inversion process for large-scale TDEM datasets. Several authors have proposed 3D inversion approaches for large AEM datasets that account for the limited sensitivity volume of each transmitter location, allowing for more efficient 3D inversion that limits the spatial footprint of the EM system as it moves across the survey area using a moving footprint or local mesh algorithm (Cox et al., 2010; Yang et al., 2014).

While these inversion approaches have significantly enhanced the resolution and reliability of subsurface resistivity models, their full potential lies in their integration with hydrogeological modeling frameworks. In particular, probabilistic inversion methods enable the propagation of uncertainty into groundwater flow simulations, supporting more robust predictions of aquifer behavior. These emerging connections between EM inversion and hydrogeological applications are discussed in Section 2.5.

2.4. Open-source frameworks

When compiling the list of documented, open-source code projects for forward and inverse EM modeling (see Table 1), we noticed that the quality of documentation, ease of use, and maintenance efforts vary among software repositories. However, available open-source software ecosystems provide not only access to cutting-edge EM modeling and inversion software but also encourage collaboration and innovation within the international academic and industrial community. Some software frameworks are designed for a variety of methods, while others are optimised for specific EM methods such as AEM, ground-based EM, FDEM, TDEM, CSEM and MT methods. For instance, it could be said that AEM is a field method that requires a significant financial investment, and the process of inverting the resulting datasets necessitates expertise. Therefore, it was often not seen as a realistic method for most of the academic and industry communities. However, it is worth noting that in recent years, there have been efforts to address these concerns from a software perspective: several open-source software solutions (e.g., *custEM, GeoBiPy, GA-AEM*; see Table 1) have been used in joint collaborative projects with academia, geological surveys and industry, resulting in many hydrogeophysical studies utilising AEM (see Section 3). Another important aspect of code availability is that nowadays many easy-to-use codes to model conceptual EM problems (especially in 1D and 2D) are available, and some of them come with many examples and tutorials (e.g., *empymod*), have a graphical user interface (e.g., *EMagPy*) or are designed as plug-ins for GIS software (e.g., *EEMverter*). It is hoped that even researchers, institutes and companies with limited budgets will be able to use them for basic calculations, which are mostly very relevant in the survey design stage, to investigate if a certain EM method is suitable for their hydrogeological target. It is possible that this could result in significant cost savings, while also offering valuable insights into the method's capabilities and expectations regarding resolution.

2.5. Bridging advanced EM modeling and hydrogeological applications

Recent advances in computational EM modeling, including HPC, ML, and probabilistic inversion, have significantly improved our ability to resolve complex subsurface structures (Newman, 2014; Werthmüller et al., 2021; Castillo-Reyes et al., 2023a). However, a key challenge remains in translating these advances into actionable hydrogeological insights, as aligning EM-derived information with groundwater modeling frameworks is still complex. Bridging this gap requires integrating EM forward and inverse modeling with data-driven and physics-based approaches that directly inform groundwater system characterization and prediction.

ML has emerged as a powerful tool in EM modeling, particularly for accelerating forward simulations and inversion procedures. Neural network-based forward solvers and surrogate models can approximate traditional numerical simulations with high accuracy while significantly reducing computational costs (Moghadas et al., 2020; Li et al., 2026; Bording et al., 2021; Asif et al., 2022a). Beyond computational efficiency, ML provides a framework to directly link EM responses to hydrogeological parameters. ML algorithms can analyze large EM datasets and identify patterns and relationships that are not readily apparent through conventional approaches, improving subsurface characterization and enabling predictive groundwater modeling (Nearing et al., 2021; Chen et al., 2022; Zaresefat and Derakhshani, 2023; Huang et al., 2025). This capability supports near real-time estimation of hydrogeological variables and enhances decision-making in groundwater management.

Bayesian and probabilistic inversion methods represent another major advance, offering a framework for uncertainty quantification in EM imaging. Unlike deterministic approaches, these methods generate ensembles of plausible subsurface resistivity models and explicitly account for the non-uniqueness of the inverse problem (Gunning et al., 2010; Minsley et al., 2021; Blatter et al., 2019). The resulting uncertainty estimates can be directly propagated into hydrological modeling, improving predictions of groundwater flow, recharge, and contaminant transport (Hauser et al., 2018; Christensen et al., 2017; Faghih et al., 2024). Advances in HPC now make such probabilistic inversions feasible for large-scale EM datasets, enabling uncertainty-aware groundwater modeling workflows (Shalf et al., 2011; Asgari et al., 2022).

Emerging approaches increasingly focus on coupled or iterative workflows that integrate EM inversion with hydrogeological simulation. In such frameworks, resistivity models derived from EM data are transformed into hydraulic parameters using petrophysical relationships and subsequently used in groundwater flow models. Coupled hydrogeophysical inversion approaches simultaneously integrate geophysical and hydrological data, improving model consistency and predictive capability, although they remain computationally challenging (Hinnell et al., 2010; Pollock and Cirpka, 2012; Zebaze et al., 2025; Kouadio et al., 2023). Recent studies demonstrate that combining EM data with hydrological observations, such as streamflow and groundwater levels, significantly improves model performance compared to using EM data alone (Pleasants et al., 2025). Sequential approaches, where EM-derived structures constrain hydrological models, also remain widely used and effective for large-scale groundwater applications.

A critical component of this integration is the translation of electrical properties into hydrogeological variables. Electrical resistivity is strongly linked to properties such as porosity, permeability, and fluid salinity, making EM methods particularly suitable for groundwater investigations (Slater, 2007). Petrophysical relationships, such as Archie's law and its extensions, provide a quantitative link between resistivity and hydrogeological parameters (Archie, 1942; Waxman and Smits, 1968). Recent approaches combine these relationships with probabilistic and data-driven methods to improve robustness and reduce uncertainty in heterogeneous subsurface environments.

Overall, the integration of advanced computational EM methods with hydrogeological modeling is progressively transforming EM geophysics from a purely imaging-oriented discipline into a predictive framework for groundwater systems. In this context, the synergistic combination of HPC, ML, and probabilistic inversion techniques enables the development of uncertainty-aware, data-driven, and computationally efficient workflows (Castillo-Reyes et al., 2025). These methodological advances are particularly relevant given the increasing complexity of subsurface environments and the demand for higher-resolution imaging, which pose significant computational challenges. HPC plays a pivotal role in addressing these limitations by providing the computational resources required for large-scale simulations, and by leveraging emerging exascale architectures (Shalf et al., 2011), it becomes feasible to perform simulations that were previously intractable. This capability, in turn, enhances sensitivity analyses, allowing for more refined model parameterization and improved accuracy in subsurface characterization (Asgari et al., 2022). Furthermore, the integration of HPC with ML and AI has facilitated the development of multiscale modeling strategies that bridge large-scale geological structures with fine-scale heterogeneities. Such hybrid approaches enable a more comprehensive representation of groundwater systems by simultaneously capturing macroscopic trends and microscopic processes. For instance, Kang et al. (2022) demonstrated the use of AEM data to resolve large-scale groundwater structures in California's Central Valley while refining smaller-scale features critical for accurate flow modeling. Collectively, these developments pave the way toward fully coupled hydrogeophysical frameworks that integrate geophysical, hydrological, and geological data, ultimately enhancing the understanding of groundwater systems and supporting sustainable water resource management.

3. State-of-the-art hydrogeophysical studies

Groundwater system imaging with geophysical methods, also called 'hydrogeophysics', is scientifically aligned with the fields of biogeochemistry, ecology, and near-surface geophysics (Binley et al., 2015). Interdisciplinary projects such as Dynadeep (Massmann et al., 2023; Skibbe et al., 2024) and FRESHEM (Van Baaren et al., 2018) are examples of joint efforts for holistic aquifer characterisations through integrating different data types, such as hydrological, geochemical, biogeochemical, microbiological and geophysical data.

State-of-the-art hydrogeophysical studies using EM techniques commonly perform AEM surveys (e.g., Siemon et al., 2009a; Schamper et al., 2013; Bedrosian et al., 2016; Auken et al., 2017) that enable not only large-scale but also dense coverage of an area of interest. The specific hydrogeological application dictates the required scale, spatial resolution, and Depth Of Investigation (DOI). The DOI depends on the subsurface resistivity distribution and the characteristics of the employed system (Siemon et al., 2009b). Typical depths of investigation range from some tens of meters (conductive grounds) to several hundred meters (resistive grounds). For dual-coil FDEM systems, the DOI is shallow to medium (about 1–100 m); for TDEM, the DOI is medium-deep to deep (about 10–500 + m); for general low-frequency controlled- and natural-source EM, the DOI can reach several kilometers. However, it is worthwhile to note that the choice of EM method is highly site-specific and depends on the hydrological target, the required spatial and temporal resolution, where the survey is conducted, and the availability of financial resources. For example, limitations of AEM are that it, firstly, may be less suited for targets that require temporal resolution. Recent examples of repeat surveys exist (Kang and Knight, 2022; Hauser et al., 2025; Signora et al., 2026), and the data processing requires new methodological advancements to make reliable conclusions about the temporal evolution. Secondly, the cost related to AEM surveys, both in logistics and

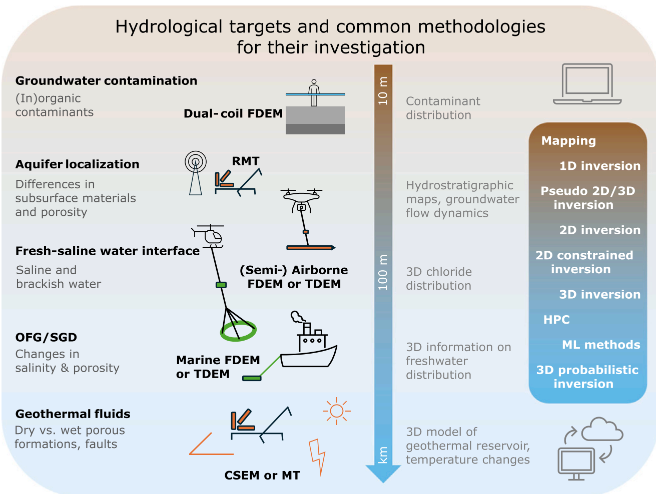

Fig. 2. Hydrological targets discussed in this review and common EM geophysical and computational methodologies for their investigation. CSEM: controlled-source EM, FDEM: frequency-domain EM, HPC: high-performance computing, ML: machine learning, MT: magnetotellurics, RMT: radio-magnetotellurics, TDEM: time-domain EM, OFG: Offshore freshened groundwater, SGD: Submarine groundwater discharge.

(computational) expertise, may not be suited to address the questions related to a hydrogeological problem.

This section focuses on recently published EM studies performed to help answer groundwater-related questions. We identify the state-of-the-art measurement techniques and evaluation methods applied to address and investigate different hydrological objectives and targets as reflected in the following subsections and Fig. 2.

3.1. Groundwater contamination

The electrical conductivity of groundwater is defined by the presence of dissolved or suspended particles (i.e., minerals and/or inorganic and organic compounds). For this reason, non-invasive EM methods are an ideal geophysical tool to detect contaminants and monitor their movement. Soluble pollutants can increase the conductivity and generate a strong contrast (Bortnikova et al., 2011). Oil and organic contaminants decrease electrical conductivity, typically with a smaller contrast than soluble pollutants (Manstein and Scozzari, 2016). The lateral variation of electrical conductivity in the subsurface can be estimated and interpreted to assess the concentration of these pollutants in the soil and groundwater.

There are various sources of groundwater contaminants (cf. Fig. 3): natural sources such as lead, copper, mercury, uranium, and arsenic; anthropogenic sources such as leaks from landfills, graveyard leachate, and septic systems; leaks from hazardous waste dumpsites; chemicals used for agricultural purposes; petroleum; leaks from surface containers of chemicals; waste from mining activities; and many others (Igboama et al., 2022).

EM measurements also allow the monitoring and interpretation of remediation measures. Wang et al. (2015) presents an example where dual-coil FDEM is used to define the soil contamination distribution in combination with GPR and ERT measurements, as well as in the evaluation of remediation results. Høyer et al. (2019) used dual-coil FDEM measurements integrated with DC/IP and geological data to assess the risk of landfill leachate presence in a geological model.

More recent studies also show applications of EM measurements and hydrological information to define contaminant distribution in the subsurface. Some examples are: Osinowo et al. (2020), who evaluated the level of subsurface leachate contamination plume generated by indiscriminate dumping of cassava product processing effluents and wastes around a dumpsite near a cassava processing mill at Ilero, southwestern Nigeria. Deidda et al. (2022) mapped an abandoned waste disposal site on the central-eastern coast of Sardinia (Italy) to delineate the extent of the landfill. Devi et al. (2020) present 3D resistivity models obtained through 3D joint inversion of ERT and RMT data using the *AP3DMT-DC* code. The models contribute to determining groundwater flow direction and estimating groundwater contamination around a waste disposal site in Northern India. Hansen et al. (2024) use towed transient electromagnetic (tTEM) resistivity mapping in combination with geochemical sampling and geostatistical modeling to identify zones with potential for groundwater denitrification in selected catchment areas in Denmark. Low-resistivity signatures typically indicate clay-rich, reducing environments conducive to nitrate

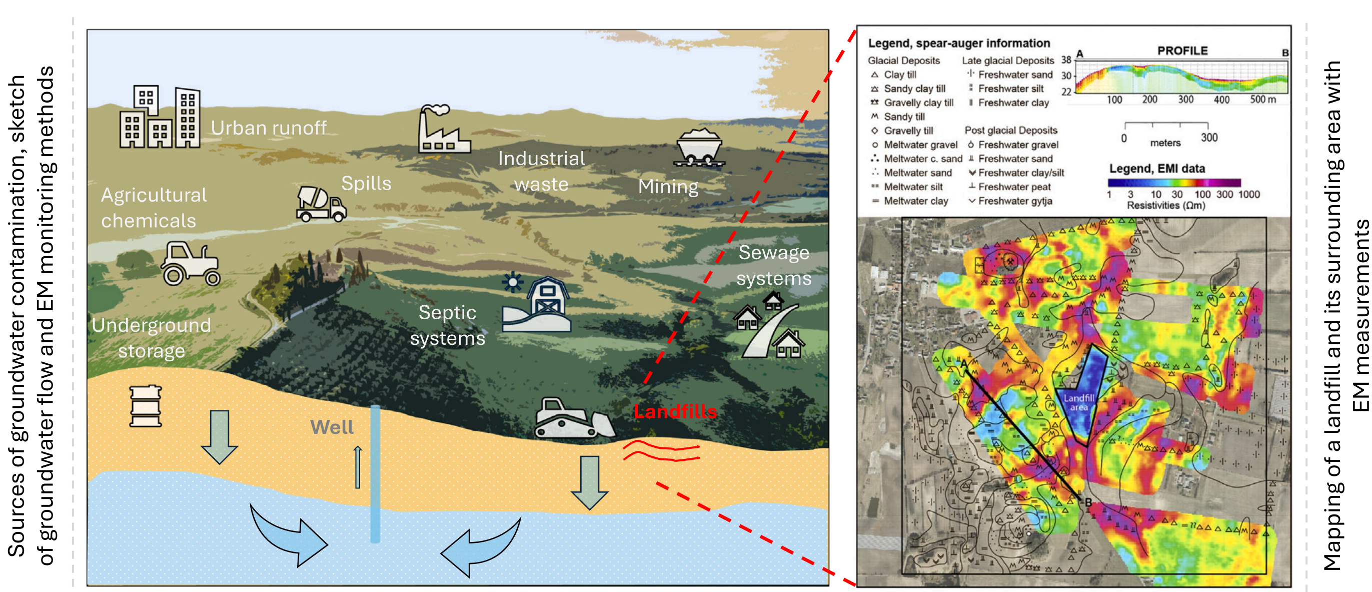

Fig. 3. Schematic figure illustrating possible sources of groundwater contamination (left) and electrical resistivity map of a region including a landfill area (right; from Høyer et al. (2019) with permission from the publisher under License number 6080170911462). The landfill is characterized by low resistivities.

removal, whereas high-resistivity zones suggest oxidizing conditions with limited denitrification capacity. Integrating tTEM-derived resistivity data with nitrate leaching models allows for spatially targeted nitrogen regulation, enhancing the effectiveness of agricultural mitigation strategies.

3.2. Aquifer localisation and characterisation

EM methods are efficient for locating aquifers, identifying their depth, thickness and lateral extent, distinguishing between confined and unconfined aquifers, understanding potential salinity gradients, and mapping the interfaces between different hydrogeological units with contrasting electrical conductivities. Moreover, structural features essential for understanding the local hydrogeology can be mapped, such as faults or barriers within aquifers or paleochannel structures with distinct material properties. For example, Mikucki et al. (2015) have used airborne EM in Antarctica to find high-conductivity lenses below resistive glacier ice or dry permafrost, indicating the occurrence of groundwater in Antarctica. Their results showed two different basins without connection, within the depth limitation of the AEM survey (approximately 350 m). Other studies used EM to find groundwater pathways through fractures (Chandra et al., 2019) or near-surface reservoirs (Rulff et al., 2025), to understand the distribution of fine-grained materials in an aquifer (Li et al., 2024) or to distinguish clusters of common hydrostratigraphy required to construct a nitrogen-retention map (Christiansen et al., 2023).

Spatial resistivity distributions provide indications of the characteristic resistivity values for different hydrogeological units (Grombacher et al., 2022) and can therefore be used to estimate hydrogeological parameters of interest, the so-called derived products, in different ways (Christensen and Christiansen, 2021). More advanced analysis methods have been developed to integrate geophysical data of varying age, type, and quality into regional-scale hydrostratigraphic maps (Vilhelmsen et al., 2019a). Deriving the spatial distribution of hydraulic conductivity needed for groundwater-flow models requires a petrophysical or other relationship to link geophysical parameters to hydrologic properties. In Ikard et al. (2023), such a nonlinear relation between subsurface resistivity and aquifer transmissivity, compiled from aquifer tests, is established. The petrophysical relation is used to transform the EM resistivity to transmissivity, and hydraulic conductivity over areas where the saturated thickness of the aquifer is known.

The EM method can also be used to understand dynamics, such as seasonal or anthropogenic changes in groundwater storage. However, these changes are often subtle and require high-quality data acquisition. For example, in TEM monitoring, the noise source from 3–300 kHz radio waves should be addressed with appropriate stacking (McLachlan et al., 2023). In recent years, an upward trend has been observed in monitoring studies with EM technology. For example, Zamora-Luria et al. (2023a) demonstrate the use of TEM to monitor water table variations in shallow unconfined aquifers. Xiao et al. (2022a) have developed a 3D time-lapse inversion code for TEM, which could be further modified for groundwater studies.

Airborne EM methods are most frequently used for hydrogeological applications (Siemon et al., 2009a; Auken et al., 2017; Minsley et al., 2021, and references therein), as they are the only practical methods for large-scale mapping of aquifers with adequate spatial coverage (Fig. 4). The depth of investigation is generally superior to other systems, due to their large transmitter moments. However, inaccurate logging of the flight altitude, tilt, and roll can complicate data processing and inversion. This is addressed, for example, with an additional flight altitude parameter in the inversion (Auken et al., 2015). While AEM surveys are currently primarily single-time measurements, recent advances have begun to address the challenge of increasing temporal resolution through repeat (time-lapse) AEM datasets. Hauser et al. (2025) introduce a time-lapse inversion that fixes model parameters not expected to change between surveys, and penalises model changes. Applied to one frequency-domain and two time-domain surveys over the Bookpurnong floodplain in South Australia, their approach produces fewer artefacts and more hydrologically plausible freshwater–saltwater interfaces compared to independently inverted surveys. Signora et al. (2026) further develop a time-lapse AEM inversion scheme, focusing on the problem of non-coincident flight lines and different acquisition systems across surveys.

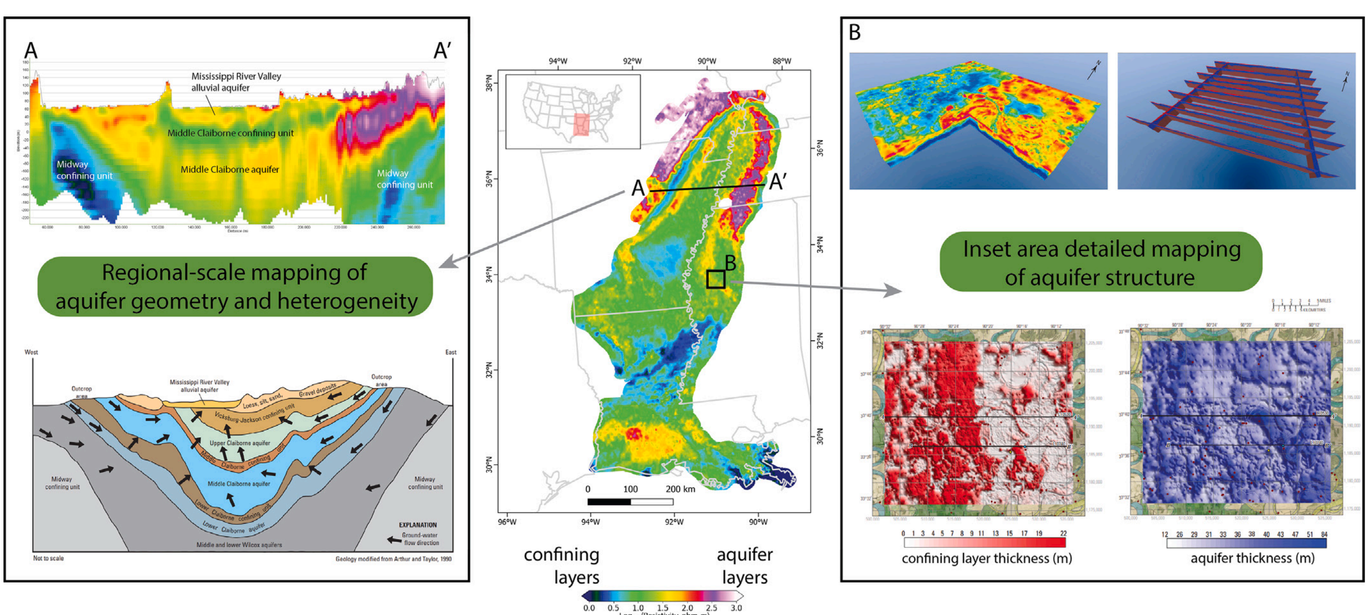

Fig. 4. Examples of regional and detailed aquifer localisation and characterisation using airborne EM data. (Middle panel) resistivity slice from 70–75 m depth showing regional-scale aquifer structure, highlighted along cross-section A–A' (Minsley et al., 2021) and compared with basin conceptual model section from Hart et al. (2008) at left. High-resolution inset area details aquifer structure and heterogeneity in three dimensions (upper right) with interpretations of three-layer model summarized as confining layer and aquifer thickness maps (lower right) from Burton et al. (2020).

Towed systems, such as a tTEM (Auken et al., 2019; Maurya et al., 2020), or floaTEM (Maurya et al., 2022) or a DualEM mounted behind a quad or car (Koganti et al., 2018) are especially suited for the medium scale, but require accessible field conditions. Towed systems generally have better vertical and horizontal resolution in the upper part of the subsurface compared to airborne systems primarily due to the smaller footprint and denser data sampling (Maurya et al., 2023). Lane et al. (2020) compare results from airborne FDEM measurements with floaTEM data for mapping beneath stream systems.

In the (near) future, drones will be used on inaccessible terrains. Such systems are currently being built and tested (Nyboe et al., 2024), while legal and system design challenges persist. Semi-airborne methods, consisting of a source on Earth's surface and a light receiver on a drone, are currently the most viable drone applications for EM, but these are currently mainly intended for mineral exploration and imaging deep structures (Kotowski et al., 2022). While (semi-)drone systems have great potential, they are still in the experimental stage for groundwater EM applications (Maurya et al., 2024; Blanco-Arrué et al., 2024).

On a small scale, groundwater investigations with EM instruments involve lower costs. For example, Gaona et al. (2019) have used a dual-coil FDEM multi-receiver to infer texture changes in the sediment. This capability is useful for identifying streambed structures relevant to groundwater and surface water connectivity. Near-surface mapping surveys have become quite common, e.g., to map clay content variation (Triantafilis and Lesch, 2005) or soil compaction (Carrera et al., 2024). In order to combine geophysical data for groundwater investigations on small scales, petrophysical relations are commonly used (Garambois et al., 2002; Vizheh et al., 2020). The combination of spatial mapping and time-lapse monitoring can push the state-of-the-art further. For example in agricultural processes, time-lapse surveys can uncover variable states, such as the soil moisture content. This can help study soil drying processes or water uptake in compacted soils or beneath different plant genotypes (Blanchy et al., 2020; Shanahan et al., 2015). Time-lapse FDEM can save costs compared to soil sampling. The complexity of the relation between electrical conductivity and different soil properties remains an impediment and currently requires a joint interpretation with numerical hydrological simulations (Farzamian et al., 2021). For TDEM, monitoring surveys are less common. Zamora-Luria et al. (2023a) recently monitored water table variations in a shallow unconfined aquifer. Regularization proved key to ensuring the recovery of a smoothly varying water table. The method could achieve a 0.4 m resolution between 10 m and 30 m depth.

3.3. Fresh-saline water interface

Saltwater intrusion is a critical environmental challenge affecting freshwater aquifers worldwide, where saline water infiltrates and compromises water quality and ecosystems. This process is primarily driven by the density difference between saline and fresh water, whereby less dense fresh groundwater lies above denser saline groundwater, resulting in the formation of (often shallow) freshwater lenses (Delsman et al., 2018). Furthermore, historical events—such as storm surges, changes in sea-levels, and tectonic activity— can result in the natural deposition of saline groundwater (van Engelen et al., 2018; Delsman et al., 2014). Human activities and environmental changes can disrupt the natural pressure balance that, for example, limits the inland movement of saltwater in low-elevation coastal zones. As a result, reverse groundwater flux from the ocean to land can occur. This phenomenon can be seen, for example, in the excessive pumping of fresh groundwater, which can lead to the upconing of saline groundwater and the resulting extraction of brackish or saline groundwater (Werner et al., 2013). The interaction between freshwater and seawater in coastal regions is a complex subject of study that requires a multidisciplinary approach (Weymer et al., 2022) combining the expertise of geophysicists, hydrogeologists, (bio)geochemists and modellers' (Arévalo-Martínez et al., 2023).

Detailed, local studies of the fresh-saline water interface can be performed with ground-based methods. Levi et al. (2008) performed a feasibility study across the Judea Desert using a deep-penetrating TDEM system to reach depths of 1.5–2 km. They interpreted the soundings with 1D layered resistivity inversion at each site to delineate deep fresh, brackish and saline groundwater bodies and compared them to electrical logs and direct water salinity measurements. In a more recent study, Pondthai et al. (2020) collected nearshore TDEM soundings to image the fresh–saline interface of a coastal carbonate aquifer southeast of Malta. One-dimensional inversion places the onshore freshwater lens at roughly 4–24 m depth above seawater-saturated layers, thickening landward from the coast, and 2D and 3D finite-element electromagnetic forward models are used to better constrain the subsurface geometry of this freshwater body.

Fresh-saline groundwater distributions are often studied with airborne EM methods (e.g., Ball et al., 2020; Rahman et al., 2021; King et al., 2022; Blanco-Arrué et al., 2024) to enable the practical imaging of larger areas compared to ground surveys (Nenna et al., 2013; Abdalla et al., 2010), especially where studies bridge onshore-offshore domains. For example, Ball et al. (2020) mapped the fresh, saline and brackish groundwater in the San Joaquin Valley, California by evaluating their airborne TDEM data with 1D laterally constrained (Aarhus Geosoftware, Auken et al., 2015) and Bayesian (GeoBIPy, Minsley et al., 2020) inversions. They base their interpretation on local groundwater quality sampling and provide joint uncertainties for their models. Through calibration, resistivity models can be converted into salinity distributions: For example, Rahman et al. (2021) developed a method to derive chloride concentrations from borehole information and helicopter-borne EM (HEM) data. In the following, we introduce two ongoing state-of-the-art projects that aim to image the fresh-saline water interfaces with EM geophysics.

The **FreshEM Zeeland** (NL) project, which was flown in 2015, aimed to investigate the distribution of freshwater and saltwater in the south of the Netherlands (Zeeland) using helicopter-borne frequency-domain (six frequencies) EM measurements with the RESOLVE system operated by the German Federal Institute for Geosciences and Natural Resources (BGR). The survey encompassed 9640 flight kilometers and yielded 14.4 million data points. State-of-the-art technologies were developed and applied within the project, e.g., in translating 1D resistivity models into a consistent 3D salinity model while assessing its uncertainties. 3D geological data, sediment samples (Revil et al., 2017) and empirical resistivity vs. water salinity relationships were used to convert the 1D resistivity inversions into a quantified estimate of salinity, represented as mg/l chloride (cf. Fig. 5). The approach used stochastic methods to understand the forward propagation of error, which highlighted the relative contribution of uncertainty for each sequential processing step, including spatially, to map regions of uncertainty in the resulting model. Here it was found that the inversion step was the largest contributor to uncertainty, and that delineating the lateral and vertical positioning of the fresh-saline interface was the least certain part of the resulting 3D model. This was corroborated by King et al. (2018), where inversions were quantitatively tested and compared using the same survey data. Here a comparison of smooth, multi-layer inversions (Constable et al., 1987; Farquharson et al., 2003) and layered, few-layer inversions (Auken and Christiansen, 2004), commonly used to evaluate frequency domain AEM data, found that the choice of regularization (or smooth vs. sharp methods) caused significant uncertainty, and frequently overestimated the thickness of the resulting brackish zone. A related synthetic study (King et al., 2022) attempted to address these shortcomings using the integration of AEM monitoring surveys into groundwater flow models. The presented novel approach uses repeated AEM surveys and 3D variable-density groundwater flow and salt transport modeling to jointly improve the parameterization of the variable-density groundwater flow models while simultaneously providing a detailed 3D map of groundwater salinity distributions. This approach is, while only synthetic, computationally

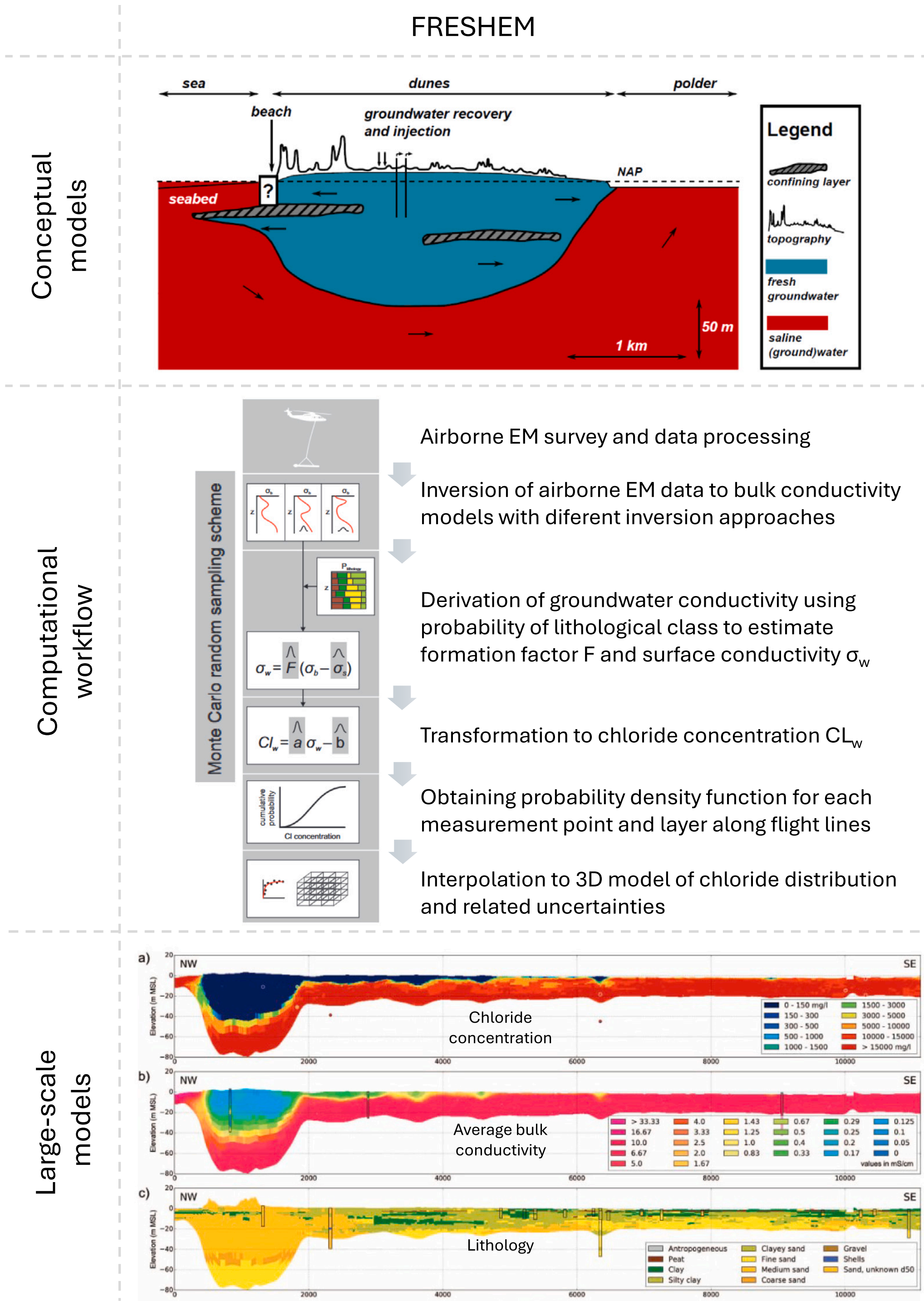

Fig. 5. General approach in the FRESHEM project to obtain salinity models from airborne EM data: The conceptual model (upper row) shows the expectations of groundwater salinity distribution along the Dutch coast (Van Baaren et al., 2018), the computational workflow (middle row) combines conductivity models (lower row b) with lithological information (lower row c) to obtain large-scale groundwater salinity models (lower row a). Figure modified after Delsman et al. (2018).

demanding. As a result, a suggested improvement is the utilisation of distributed memory parallelization for faster computation times (Verkaik et al., 2021), which can be implemented using HPC. The FreshEM project is due to continue in 2025, aiming to map both deeper sediment and shallow fresh-saline distributions across a large portion of the Netherlands. The data will largely be processed using the same base workflow as Delsman et al. (2018), with additional research being undertaken to improve inversion methods and examine the usefulness of data-fusion methods (e.g., Zuada Coelho and Karaoulis, 2022). Furthermore, re-flights have been planned over the same survey lines of the 2015 survey, resulting in the opportunity to potentially map groundwater changes over time, and ultimately test the coupling of numerical groundwater models (e.g., King et al., 2022) using real data.

The **Blue Transition** project is a major EU-funded initiative focused on addressing water management challenges in the North Sea region of Europe. Besides many other environmental topics, Blue

Transition studies groundwater salinization by conducting geophysical measurements, drillings, geotechnical monitoring, and modeling (The-Blue-Transition-Partnership, 2024). Time- and frequency domain airborne, semi-airborne and ground EM surveys are performed by Aarhus University (DK), and the LIAG institute (GE). Günther et al. (2022) report on a semi-airborne drone-based FDEM survey, i.e., powerful transmitters on the ground and lighter magnetic field receivers in the air, for 3D imaging of groundwater salinization at a test site of the Blue Transition project. The semi-airborne method is a new methodology that enables coverage of large areas with higher penetration depths compared to traditional airborne EM, which is beneficial when examining deeper aquifers that may experience salinization through geological formations, such as salt deposits. Blanco-Arrué et al. (2024) explore groundwater salinization in the Minstedt area (GE) using the same semi-airborne approach and a multi-transmitter measurement setup. Using the custEM code (Rochlitz et al., 2023) they run multi-patch 3D inversions of magnetic field components. The multi-patch approach is a region decomposition method that aims at keeping the computational load of 3D inversion manageable. Their resistivity models delineate the fresh-saline groundwater interface between 50 and 150 m depth. Borehole logs, ERT and TDEM data will subsequently be used to cover different depths and resolution scales to feed coherent subsurface resistivity information into a comprehensive groundwater flow model that will influence the emplacement of appropriate aquifer recharge strategies such as rewetting of peat lands and infiltration in geest areas.

In summary, several EM techniques can be used to study the freshwater-saltwater interface. However, the focus is on airborne techniques. Groundwater systems are dynamic natural features, subject to time-varying salinization and freshening processes. To extend the scope of the studies to cover not only the current state of groundwater salinization but also its dynamics, time-lapse or at least repeated measurements would be essential for monitoring purposes (Van Baaren et al., 2018; Arévalo-Martínez et al., 2023).

3.4. Offshore groundwater systems

Offshore freshened groundwater (OFG) is freshwater hosted by sediments and rocks less than 300 m below the seafloor and is characterized by lower salinity than seawater, as it originates mostly from meteoric waters. Electrically resistive anomalies in offshore EM models can therefore hint at OFG resources in porous rocks (Fig. 6). Between 100,000 to 1,000,000 km^3 OFG is estimated to be globally available in continental margins but remains largely unexplored (de Moor, 2023). Geological modeling supported by drilling data can estimate the amount of OFG in local reservoirs (Thomas et al., 2023) often hosted in buried paleochannels (Mulligan et al., 2007). EM and seismic investigations can help to gain further insights into the extent and character of OFG sites (Micallef et al., 2021).

Recently, OFG systems have gained attention in the EM community and were studied with customized EM systems and advanced evaluation software: Haroon et al. (2018b) apply a novel marine differential electric dipole system to study a freshwater body beneath the Mediterranean seafloor in Bat Yam, Israel. They use 1D inversion models and a 2.5 D forward modeling study to characterize the aquifer system. Gustafson et al. (2019) study aquifer systems offshore on the U.S. Atlantic margin using marine MT and CSEM and 2D separate and joint inversion approaches (Fig. 6). Haroon et al. (2021) utilise a seafloor-towed electric dipole-dipole TDEM system called HYDRA (Schwalenberg et al., 2017, and references therein) to map freshened groundwater within carbonate margins offshore the Maltese Islands. They combine 2D resistivity models originating from the CSEM measurements with seismics and core

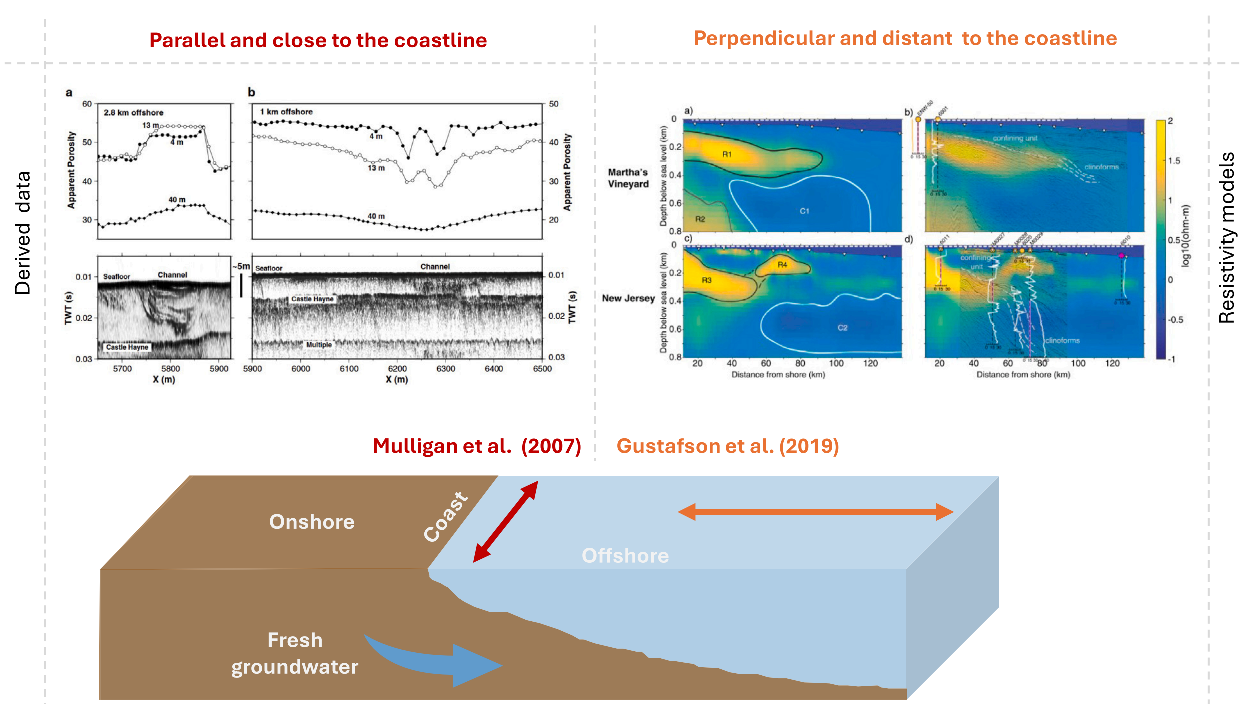

Fig. 6. Offshore freshened groundwater and submarine groundwater discharge systems can be studied with EM geophysical methods and are often guided by paleochannels. The examples shown in this figure are compiled from Gustafson et al. (2019) and Mulligan et al. (2007) (with permission from the publisher under license number 6251341118770). Both studies use EM data to collect information on offshore groundwater occurrences at different distances and angles to the respective coast of the study. Note that the apparent porosity in the upper left figure is compiled from salinity modeling and EM data. The results indicate that seawater flows into the aquifer along the channel axis, and fresher water flows out of the aquifer into the sea along the channel margins (Mulligan et al., 2007). Gustafson et al. (2019) show that by combining resistivity models (upper right figure) with other information such as seismic data or drilling logs, conceptual models and a consistent interpretation of the subsurface and the water bodies below the seafloor can be obtained.

logging data and conduct numerical hydrogeological modeling to infer the origin of localized resistivity anomalies, which appear due to either a decrease in porosity or freshwater occurrence.

A CSEM survey presented by King et al. (2022) underlines the significance of geophysical measurements for water management purposes in near-shore areas: As climate change is causing water scarcity in San Diego County, a new desalination facility is purifying brackish groundwater from the coastal San Diego Formation, but there is limited knowledge about offshore geology and groundwater quality in the adjacent continental shelf. Measurements were performed with a small surface-towed CSEM system (Sherman and Constable, 2018). The porosity range of the OFG formation and the cementation exponent in Archie's law were determined with data from monitoring wells and hydrological models to relate the bulk resistivities detected with CSEM data to the pore fluid salinities. The obtained 2D resistivity models revealed a significant volume of fresh-to-brackish groundwater in the continental shelf, indicating potential pathways for saltwater intrusion and the importance of understanding offshore geology for the longevity of desalination facilities.

The interdisciplinary SMART initiative (Helmholtz-Association, 2018) focuses on the development of techniques and methodologies for investigating OFG aiming to facilitate sustainable management of these unconventional water resources. The participating research institutes use the newly developed SWAN device, a modular surface-towed TDEM and FDEM system (Pastoressa et al., 2023; Haroon et al., 2024) that can be used in different modi: in-line measurements, where transmitters and receivers are towed behind a vessel, 3D measurements, where one vessel tows transmitters and receivers and additional vessels tow only receivers or amphibious measurements, where the transmitter is placed onshore and receivers are towed offshore. The SWAN system is suited for surveys in water depths less than 100 m and the DOI is approximately 150–200 m.

A CSEM survey with the SWAN system was conducted by Micallef et al. (2020) to investigate the OFG distribution in the Canterbury Bight, New Zealand. To infer the pore-water salinities and subsequently the geometry, heterogeneity, controls and geologic history of the OFG bodies, they integrate controlled-source EM and seismic reflection results with borehole data and hydrological modeling. Faghih et al. (2024) evaluate this dataset with 2D deterministic and 1D Bayesian inversion approaches. The latter provides uncertainty estimates for the obtained resistivities, which are used to constrain the prediction of pore fluid salinity distributions. Lohrberg et al. (2024) discuss the role of large subsurface landforms formed beneath ice sheets in the Pleistocene and their potential as preferential flow pathways of OFG in so-called tunnel valleys in the southeastern North Sea. The study used marine TDEM data acquired with SWAN to investigate if the distribution of electrical resistivities indicates the presence of OFG in the tunnel valleys whose boundaries can be delineated with seismic reflection data.

In a more recent study, Faghih et al. (2025) discusses the benefits of complementing conventional 2D deterministic inversion with trans-dimensional Bayesian inversion applied to marine CSEM data from a semi-arid carbonate site off Gozo to improve characterization of OFG. While the deterministic approach yields a smooth best-fit resistivity model, the Bayesian method provides localized probabilistic insights, resolves strong resistivity contrasts, and quantifies uncertainties in resistivity and layer thickness, revealing small-scale variations that 2D models may miss. Discussing both methods shows key similarities and differences, with posterior probability distributions offering clearer resolution where 2D sensitivity is low—particularly for deeper anomalies and 1D resistivity variations. Overall the results confirm the presence of an OFG body in the Gozo region and demonstrate the effectiveness of marine time-domain CSEM for distinguishing fresh versus saline pore-water in complex carbonate environments.

Wu and Yuguo Li (2024) presents a model of the Shengsi paleochannel in the Yangtze River estuary, investigating the potential of marine controlled-source electromagnetic surveys to detect thin, high-resistivity layers associated with offshore freshened groundwater. Using geoelectric models derived from well logs and conceptualised forward CSEM modeling, the authors demonstrate that, for paleo-channel freshwater bodies at target depths, realistic transmitter-receiver geometries and frequency ranges produce measurable responses. They conclude that CSEM is a feasible reconnaissance tool for locating offshore freshwater in this setting, recommending the integration of EM with seismic and borehole data to ensure reliable mapping and validation. Le et al. (2024) report a magnetotelluric study using 25 stations along a 120-km transect in the Pusur River, Coastal Bangladesh, converting resistivity models into salinity estimates via Archie's law to target deep, high-resistivity Pleistocene freshwater bodies beneath saline shallow aquifers. Computationally, the authors performed 2D regularized nonlinear inversion using MARE2DEM, then quantified non-linear uncertainty with parallel-tempered reversible-jump MCMC 1D Bayesian sampling, demonstrating robust detection limits, resolution thresholds for thin resistive layers, and the value of integrating Bayesian and smooth inversions for uncertainty assessment.

A hydrological phenomenon connected to OFG is submarine groundwater discharge (SGD). The discharged waters consist of fresh groundwater, re-circulated seawater, or a mixture of both and originate from the flow of fresh and brackish water from land to the ocean passing through continental and insular margins. The control mechanisms of SGD systems are complex and range from hydraulic gradients between land and sea to tidal and wave-related forces, density-driven flow and seasonal variations in water table height (Taniguchi et al., 2019). As the biogeochemical processes in SGD systems play an important role in coastal ecosystems, they are mainly subject to geochemical water analysis and tracer tests (Santos et al., 2021). EM methods are useful for mapping SGD systems on regional scales because spatial variations in pore water salinity are a primary driver of resistivity changes within these systems (Taniguchi et al., 2019).

A state-of-the-art survey to investigate SGD was presented by Paepen et al. (2020). Bridging land and marine environments, they conducted FDEM and electrical surveys in the intertidal zone, upper beach, dunes, and shallow coastal area to investigate submarine groundwater discharge. Resistivity models from their ERT data identified zones of fresh submarine groundwater discharge originating from a potable freshwater lens below the dunes, flowing underneath a thick saltwater lens from the dunes to the lower sandy beach. FDEM mapping displayed the lateral variation of the discharge zone and revealed discharge at the same locations. A repeated FDEM survey suggested that freshwater discharge is stronger at the end of winter compared to the beginning of autumn. However, interpreting the results quantitatively in a high-salinity context is challenging due to the loss of resolution below the conductive saline lens. In a subsequent study, Paepen et al. (2022) used an appraisal tool to address the resolution issues by applying estimates of uncertainty in model resolution, sensitivity, and depth of investigation found from field-informed synthetic modeling and inversion to results of the field data inversions.

Attias et al. (2021) used marine frequency domain CSEM to study the hydrological system off the coast of west Hawai'i. By employing 2D inversion and keeping the water column in the inverse domain, they detected large-scale vertical freshwater plumes originating from subsurface layers with freshened water as well as extensive surface freshwater areas. Hoffmann et al. (2025) analyzed the karst aquifer system in the urban regions of Antalya, Türkiye, with an exemplary multi-method geophysical approach, including onshore FDEM and TDEM methods. Their findings reveal that groundwater flows into the sea via coastal and submarine freshwater springs, but is threatened by saltwater intrusion. The main beach area of Antalya is characterized by diffuse groundwater flow, while channelized flow occurs along the cliffs where submarine springs are found. These springs alter salinity levels in the water and expose the underlying carbonate aquifer, creating varied habitats on the seafloor.

A helicopter-borne TDEM survey flown with SkyTEM (Auken et al., 2009) in the McMurdo Dry Valleys region of Antarctica detected connections between inland lakes, aquifers, and subglacial waters (Foley et al., 2019). These waters are saline, may contain high concentrations of important dissolved ions like iron and silica, and move from land to sea without recirculation of seawater. It is speculated that these waters emerge as submarine groundwater discharge along the coast, potentially delivering significant amounts of bioavailable iron and silica to the Southern Ocean. TDEM data acquired along three profiles were evaluated via laterally constrained 30-layer 1D inversion (AarhusInv, Auken et al., 2015).

The aforementioned articles reporting on state-of-the-art offshore-groundwater studies predominantly use marine TDEM and FDEM instruments, while airborne methods allow for acquiring data above land and sea to study the hydrological connection between both. 2D inversion with the Mare2DEM code (Key, 2016; Haroon et al., 2018a) is the approach that is most commonly applied to obtain resistivity models.

3.5. Geothermal fluids

The effective management of geothermal energy resources depends on a thorough understanding of groundwater distribution, salinity, and movement, all of which are critical for assessing the viability of geothermal reservoirs (Kana et al., 2015; Castillo-Reyes et al., 2024). EM techniques can help to explore and monitor groundwater resources in geothermal energy systems, where subsurface water significantly influences heat transfer.

EM methods such as MT, CSEM, and TDEM are commonly employed to investigate subsurface electrical resistivity at intermediate-to-deep scales (Munoz, 2014). In geothermal systems, the pronounced contrast between resistive dry formations and conductive groundwater-bearing zones enhances the detection of subsurface features.

For instance, MT has been widely applied in various geothermal projects to characterize the spatial distribution of groundwater at depths critical for exploitation. By utilizing natural variations in Earth's magnetic and electric fields as energy sources, MT surveys can map resistivity variations over a broad depth range, encompassing both shallow aquifers and deep geothermal reservoirs (Uchida and Sasaki, 2006; Erdogan and Candansayar, 2017; Árnason et al., 2010; Wu et al., 2012; Arzate et al., 2018; Corbo-Camargo et al., 2020; Held et al., 2020; Ruiz-Aguilar et al., 2020a; Fuentes-Arreazola et al., 2021). Similarly, CSEM has been utilized for characterizing and monitoring geothermal fluids, demonstrating its effectiveness in this context (Coppo et al., 2016; Darnet et al., 2018; Castillo-Reyes et al., 2021; Hering et al., 2022; Liao et al., 2022). Both TDEM and CSEM are often employed in conjunction with MT to enhance resolution in specific depth intervals, thus providing more detailed insights into the geothermal environment (Spichak and Manzella, 2009; Girard et al., 2015). To illustrate the potential of EM methods in evaluating geothermal fluids, Fig. 7 demonstrates the application of MT techniques to the San Felipe geothermal prospect, a previously unrecognized hydrothermal system located on the northeastern coast of the Baja California Peninsula, Mexico.

Recent studies have explored the modeling of groundwater systems using resistivity-temperature relationships (Eltayieb et al., 2023), while other research has integrated modeling with experimental data from CSEM and MT techniques to improve subsurface characterization (Castillo-Reyes et al., 2021). Notably, time-lapse monitoring has

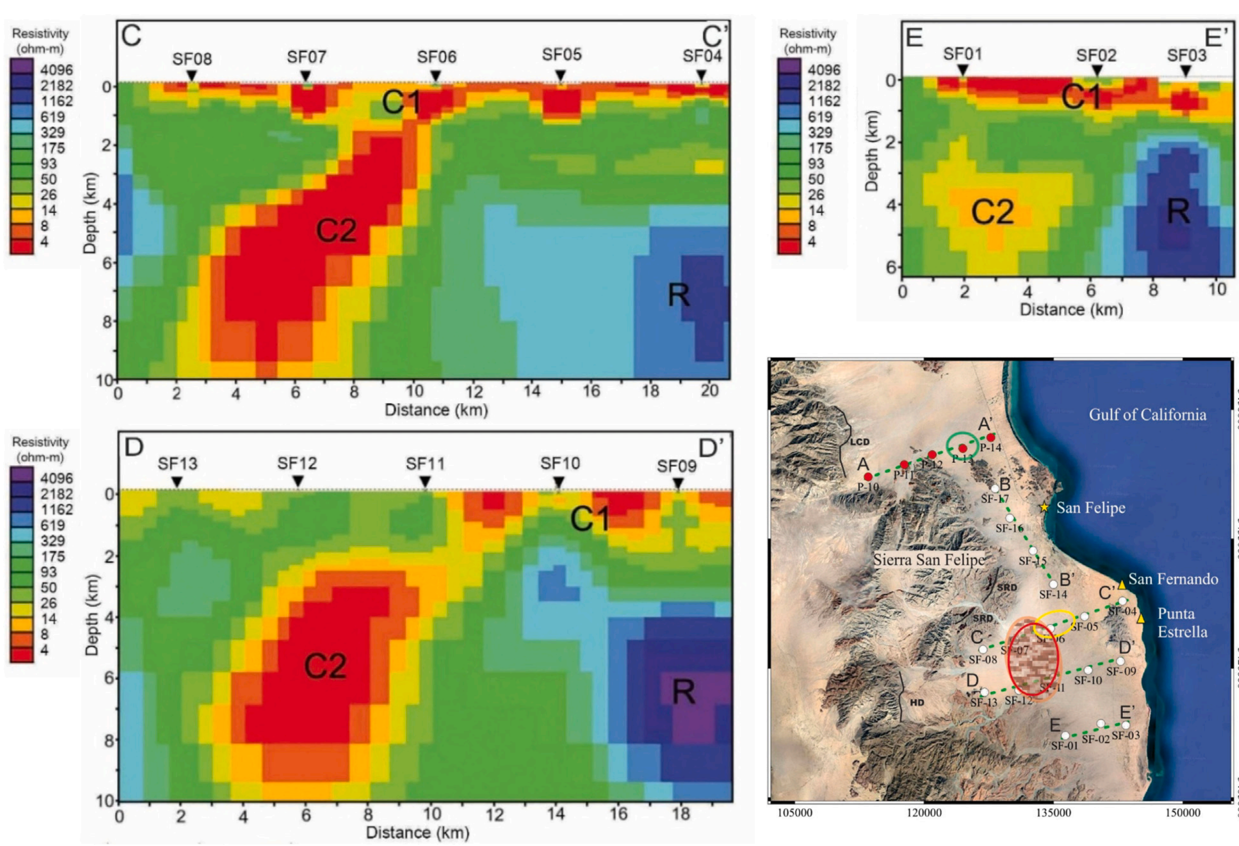

Fig. 7. MT results for the San Felipe geothermal prospect in Mexico, adapted from Prol-Ledesma et al. (2023). In the bottom-right panel, the green circle highlights a low-resistivity anomaly identified north of San Felipe in the MT profile (Pamplona-Pérez, 2007). The yellow circle marks the area of the C2 low-resistivity anomaly reported by (Ruiz-Aguilar et al., 2020b), while the red circle shows the C2 anomaly identified by Prol-Ledesma et al. (2023). Filled red circles represent MT stations, and filled white circles indicate combined MT and TEM stations; dashed green lines represent MT and TEM profiles. The remaining panels show MT profiles, indicating a shallow conductive C1 body (≈ 4 Ωm), a deeper conductive C2 body (≈ 8 Ωm), and a resistive R body (≈ 1000 Ωm).

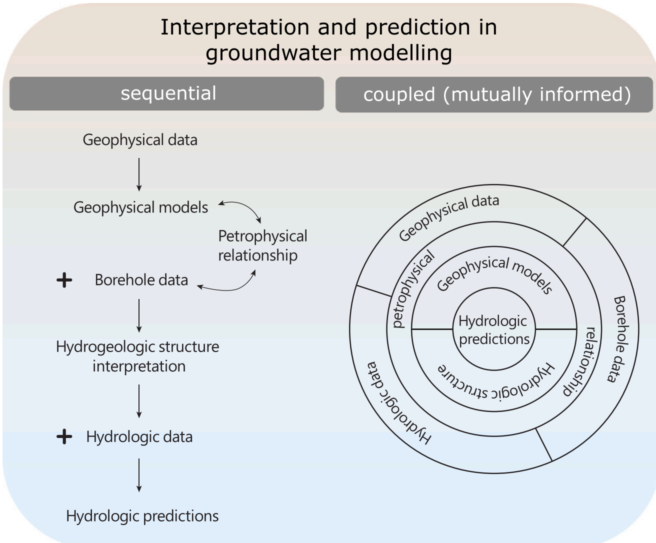

Fig. 8. Workflow diagrams for informing hydrologic predictions with geophysical data. Sequential workflows (left) interpret geophysical properties such as resistivity from geophysical data. Geophysical models are combined with boreholes or other geological information using petrophysical relationships to produce interpretations of hydrogeological structure and/or heterogeneity. Structural information is used in the development of groundwater models that make hydrologic predictions. Coupled, or mutually informed, workflows (right) involve the simultaneous integration of geophysical, borehole, and hydrologic observations together with a petrophysical relationship to jointly inform both hydrologic and geophysical model values, leveraging the combined sensitivity of all data. The resulting hydrologic model is used to make hydrologic predictions.

been effectively employed to assess changes in geothermal systems, as demonstrated in a study that utilized three-dimensional time-lapse inversion of transient EM data at an Icelandic geothermal site (Xiao et al., 2022a). Additional applications, such as evaluating geothermal heat flux in Antarctica (Foley et al., 2020) and geophysical imaging of the Yellowstone hydrothermal plumbing system (Finn et al., 2022), further illustrate the versatility of EM methods in geothermal research. Moreover, recent advancements in using towed transient EM techniques in geothermal areas of New Zealand highlight the ongoing evolution of these methods and their importance in the field (Reeves et al., 2023).

For a comprehensive understanding of the state-of-the-art EM techniques for geothermal exploration, we refer readers to the literature reviews conducted by Pellerin et al. (1996); Munoz (2014); Patro (2017); Yang et al. (2023); Castillo-Reyes et al. (2024), which provide an in-depth examination of the advancements and applications of EM methods in this field. Using EM methods for hydrothermal and magmatic system characterization in volcanic environments spans an entire research field, but goes beyond the scope of this review.

4. Feasibility for practical groundwater studies

Some hydrogeological questions can be directly assessed from the analysis of geophysical models, with several examples highlighted in Section 3 such as the presence or absence of localized confining layers that may restrict or promote recharge (Cook and Kilty, 1992; Kang et al., 2025; Minsley et al., 2021), regions of continuous aquifer materials that may be targets for drilling, patterns of elevated groundwater salinity or the fresh-saltwater interface (Ball et al., 2020; Goebel et al., 2019; Fitterman and Deszcz-Pan, 1998), or localization of offshore freshened groundwater (Gustafson et al., 2019; Micallef et al., 2020). However, a common objective in hydrogeophysical studies is to incorporate geophysical inversion results into the development of groundwater models to improve their ability to make hydrologic predictions (Mason et al., 2020; Leaf et al., 2023). An important source of uncertainty in groundwater models includes information about both geological structures and hydrologic parameter values, including heterogeneity in parameter values within those structures (Refsgaard et al., 2012). Spatially extensive and high-resolution geophysical surveys hold significant promise for reducing the geological uncertainty in groundwater models; however, there are numerous challenges and approaches to achieving this in practical groundwater studies.

Answering the common question, “did the geophysical data improve my groundwater model?” is not always straightforward because different hydrologic predictions will benefit from different types of information. For example, improving head predictions in wells can rely heavily on improving local estimates of hydrologic properties and aquifer thickness in the vicinity of those wells. In contrast, predictions of groundwater transport may rely on parameter heterogeneity as well as conceptual geological model structure such as small-scale holes in a confining layer that allow for communication between two aquifer units. Other predictions may only be weakly sensitive to geological model structure, or can be difficult to identify if other hydrologic parameters are incorrectly estimated (e.g., surface recharge or streambed hydrologic properties). Therefore, it is important to consider the types and scales of geologic information that are most valuable to the groundwater model in order to incorporate geophysical results effectively.

Approaches for integrating geophysical data in groundwater studies can be broadly split into two categories (cf. Fig. 8): uncoupled (or sequential) and coupled (Hinnell et al., 2010). In the uncoupled approach, geophysical data are first inverted, ideally with measures of parameter uncertainty. Structural interpretations may be made manually or using automated algorithms to delineate large-scale geologic or hydrostratigraphic units that may inform the layers of a groundwater model. Likewise, discrete hydrologic parameter values and parameter heterogeneity can be estimated by applying a petrophysical relationship that links geophysical properties such as (complex)electrical resistivity with hydrologic properties such as hydraulic conductivity. These interpretations of structure and hydrologic properties are then incorporated into a groundwater model, either as fixed properties used to produce hydrologic predictions, or as starting values in a groundwater model calibration that incorporates additional hydrologic observations. In the coupled approach, both geophysical and hydrologic observations are used in a simultaneous inversion to leverage the combined sensitivities of both methods. A petrophysical relationship that links geophysical and hydrologic properties can be assumed as known, or estimated as part of the coupled inversion.

Coupled inversion has the advantage of making use of both geophysical and hydrologic data simultaneously which can produce model results consistent with both types of observations. However, there are also significant computational challenges in linking these disparate data types into a single inversion, making the coupled approach far less common. Coupled hydrogeophysical inversion has been applied in studies that incorporate GPR and ERT datasets (Hinnell et al., 2010; Pollock and Cirpka, 2012), but there are few examples that use the EM methods discussed here. A recent example is provided by Pleasants et al. (2025), who directly use EM induction data, from both airborne and ground-based surveys, as calibration targets for a physics-based catchment model, alongside conventional hydrological observations such as streamflow, groundwater levels, and soil moisture. Applied to a headwater catchment in Idaho, USA, their results demonstrate that EM data alone are insufficient to constrain the hydrological model, yielding poor predictions of catchment-scale dynamics. However, combining EM data with streamflow observations substantially improves both integrated and intra-catchment predictions, approaching the performance of models calibrated with the full suite of hydrological data. This illustrates both the practical promise of EM surveys as cost-effective substitutes for dense in-situ instrumentation networks, and their inherent limitations when used in isolation, underscoring the need for careful data weighting and petrophysical parameterization in coupled hydrogeophysical inversion workflows. Earlier, Christensen et al. (2016) presented a synthetic case study that compares coupled and uncoupled inversion using AEM and borehole data, and discusses the challenges in making improved hydrologic predictions of groundwater age or recharge compared with hydraulic head. There are numerous examples of uncoupled or sequential approaches where geophysical inversions and interpretations are generated and used as inputs or constraints in a subsequent hydrologic model parameterization or calibration. AEM data are particularly well-suited for this task given the spatially extensive coverage that can be achieved at the scale of a groundwater model. For example, Marker et al. (2015) integrate AEM data with borehole lithological logs to classify hydrostratigraphic zones with hydraulic conductivity values estimated by subsequent hydrologic calibration. Koch et al. (2014) discuss the importance of quantifying uncertainty in hydrogeological models, and develop a geostatistical approach for integrating large AEM and borehole datasets to produce many realizations of model structure. Other studies have built on this concept of using EM data to quantify model structural uncertainty, but take the additional step of considering how this propagates to uncertainty in hydrologic parameter estimates and predictions, such as heads, travel times, discharge, or catchment area (He et al., 2013; Vilhelmsen et al., 2019b; Christensen et al., 2017; Hauser et al., 2018; Guo et al., 2026).

While numerous advances have been made in computational methods for interpretation of large-scale EM datasets, and for modeling large and complex groundwater systems, significant challenges remain in the fusion of geophysical data with hydrologic and borehole observations to improve groundwater model predictions. Both EM and hydrologic data are sensitive to large-scale geologic structures and heterogeneity within those structures, but inverse models that simultaneously leverage both datatypes to infer model structure and uncertainty are rare. Differences in scale of observations, sensitivity, and model parameterization make coupled inversion particularly difficult. Additionally, methods for linking geophysical and hydrologic observations and properties often rely on sparse and highly uncertain relationships derived either from petrophysical models or empirical borehole observations. Finally, geophysical methods can inform different aspects of a groundwater model, such as aquifer geometry and heterogeneity, surficial recharge, streambed conductance, or groundwater salinity. Because of the uncertainties involved at every part in the hydrogeophysical workflow, it is important that models are constructed in a way that facilitates estimates of prediction uncertainty. Consequently, all available information can be incorporated, and it can be understood what parts of a model, or what predictions remain uncertain, given existing observations and assumptions. Such a framework allows for iteratively improving groundwater models through additional data collection or refined interpretations.

In practice, geophysical interpretations must somehow be integrated into a groundwater modeling package such as MODFLOW (Langevin et al., 2024). A common practice is to use structural information derived from EM data, either as layers or zones, as well as parameter heterogeneity to inform the groundwater model structure (Vilhelmsen et al., 2019b; Leaf et al., 2023; Mason et al., 2020; Faneca Sànchez et al., 2012). Hydraulic conductivity values for different structures can be assigned based on existing knowledge of values for different units or using physical property relationships derived from co-located geophysical and borehole data. Often, starting values are updated in a hydrologic calibration using PEST or similar tools (Doherty, 2022). Groundwater models incorporate numerous inputs besides structure such as pumping, precipitation, recharge, streamflow processes, and salinity, for example. Some of these properties can also be informed with EM data, such as salinity (Faneca Sànchez et al., 2012; King et al., 2022) or recharge (Leaf et al., 2023; Cook and Kilty, 1992). Limited studies have incorporated AEM and other geophysical data in ML algorithms to make hydrologic predictions of groundwater salinity or chemistry without direct use of a process-based groundwater model (Knierim et al., 2022; Killian and Knierim, 2023).

5. Conclusions

This review synthesizes recent advances in computational methods for interpreting EM geophysical datasets with several state-of-the-art hydrogeophysical case studies. It may serve as a resource for researchers looking for i) a better understanding of how EM techniques are applied to diverse hydrological targets, ii) open-source tools for EM-data based model generation and iii) areas where computational integration across the geophysical and hydrological disciplines remains underdeveloped. In particular, the review highlights the need for developing mutually informed workflows that consistently fuse geophysical and hydrological data to reduce uncertainties in groundwater system predictions.

Interdisciplinary efforts will be essential for advancing the field of sequential and coupled hydrogeophysical inversion approaches. A key challenge is the quantification of predictive uncertainty, as many EM inversion codes rely on deterministic approaches that yield a single best-fit model without uncertainty estimates. Probabilistic inversion techniques and joint modeling frameworks — computationally demanding, but nowadays possible through HPC — offer promising alternatives, especially when informed by prior knowledge from complementary domains. Developing integrative frameworks that accommodate multi-method data and reflect the dynamics of hydrological processes can enable iterative model refinement through targeted data acquisition and improved interpretation. Achieving this vision will depend on sustained interdisciplinary collaboration and transparent communication across the fields of geophysics, hydrology, and computer science.

CRediT authorship contribution statement

Paula Rulff: Writing – review & editing, Writing – original draft, Visualization, Supervision, Project administration, Investigation, Conceptualization. **Octavio Castillo-Reyes:** Writing – review & editing, Writing – original draft, Visualization, Investigation, Conceptualization. **Wouter Deleersnyder:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **Maria Carrizo Mascarell:** Writing – review & editing, Writing – original draft, Visualization, Investigation. **Burke J. Minsley:** Writing – review & editing, Writing – original draft, Visualization, Investigation. **Jude King:** Writing – review & editing, Investigation.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Octavio Castillo-Reyes reports that financial support was provided by the Generalitat de Catalunya. If there are other authors, they 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. Electromagnetic geophysics

EM geophysical methods are used to investigate the electrical properties of the subsurface, namely electrical resistivity and dielectric permittivity. Electrical rock properties can be correlated to various aquifer properties, such as lithology, porosity, fluid saturation conductivity, permeability and hydraulic conductivity, making these methods particularly suitable for hydrogeological applications. The EM methods discussed in this review are predominantly sensitive to the electrical resistivity (ρ) which characterizes the ability of a material to impede electrical current flow and is inversely related to electrical conductivity

(σ). Groundwater typically exhibits lower resistivity compared to dry or gas-filled rocks due to the presence of dissolved ions, which can make EM surveys effective in identifying fluid-filled zones. The electrical conductivity of saturated porous sediments with low clay content can be determined via Archie's formula (Archie, 1942)– a popular empirical relationship using the rocks' porosity, fluid saturation, and fluid conductivity to estimate its bulk conductivity. Archie's formula was initially developed for clean, consolidated sands with a resistive rock matrix. To account for more complex material compositions, e.g., clay mineral content, modified versions of Archie's formula exist (e.g., Waxman and Smits, 1968).

In cases where earth materials are chargeable (often mineralization or clays), EM data can also contain induced polarization (IP) effects. If not accounted for during data evaluation, the IP effects can lead to erroneous resistivity models. Recent efforts have incorporated additional IP parameters in forward modeling and inversion algorithms (Fiandaca et al., 2012) to accurately model both the resistivity and IP parameters such as chargeability. IP modeling results in additional complexity and model uncertainty, since additional parameters are needed. However, results yield additional insight into geological properties that may not be determined by electrical resistivity alone.

Most EM instruments do not require contact with the soil and all systems operate in a non-destructive manner. Frequency-domain EM (FDEM) and time-domain EM (TDEM) induction methods use time-varying electric or magnetic fields as sources (West and Macnae, 1991). Due to the presence of conductive media in the subsurface, a secondary EM field is generated. Source and receiver instruments can be deployed at or below the surface, on-shore and off-shore and even in the air. Forward and inverse algorithms are required to simulate and evaluate TDEM and FDEM data, i.e., to connect the measured EM fields to the resistivity distribution in the area of interest (West and Macnae, 1991).

In **FDEM** techniques, the measurement geometry, the utilized frequencies and the subsurface resistivity structure control the depth of investigation as well as the possible resolution of the measurements. Diverse types of FDEM systems operating at different frequency ranges can be applied to detect the resistivity distribution of the shallow subsurface:

The use of **dual-coil** systems is very common in environmental and engineering geophysics. In this technique, two coils are used, one coil serves as a transmitter to generate a primary magnetic field and the other acts as a receiver (Siemon, 2009). Both coils are operated at a fixed distance during the survey and the coil-coil pair is moved along a survey transect. The coils orientations are usually coplanar (horizontal or vertical), but can also be perpendicular. The instrument measures the coupling ratio between the primary and secondary magnetic fields. This measurement is split into the in-phase and out-of-phase components. The depth penetration and resolution depend on the frequency and the coil geometry (Reynolds, 2011) as well as the level of measurement noise and the subsurface resistivity structure. Some instruments incorporate multiple coil-pairs with different orientations, separations, or frequencies in a single device to image over multiple depths at once.

FDEM systems that are flexible with respect to the transmitter-receiver types and their separation also exist. Very low frequency (VLF) techniques (15-25 kHz) and the radiomagnetotelluric (RMT) method (10 kHz–1 MHz) utilize distributed military and civilian radio transmitters as sources (Tezkan, 2009). In the same frequency range and below, controlled-source EM (CSEM) and natural source EM, i.e., magnetotelluric (MT), measurements can be performed. Time-series of electric and magnetic fields are measured and converted into the frequency domain, where their relationship with each other holds information on subsurface resistivities at different depths.

TDEM methods are based on the concept of generating a time-varying magnetic field by switching on and off a (constant) magnetic field in pulses (Nabighian and Macnae, 1991). One typical advantage of TDEM compared to FDEM methods is the absence of the primary magnetic field immediately after it is switched off, when the much smaller secondary magnetic fields related to the earth response can be measured. Therefore, no elimination of the primary field has to be performed at the receiver; however specific receiver coil positioning and/or bucking coils have been designed to eliminate small residual primary fields that could impact TDEM measurements. Another advantage is that TDEM systems naturally transmit and measure over a broad range of frequencies (as opposed to discrete frequencies with FDEM), resulting in sensitivity over a range of depths. However, the computational modeling for TDEM is slightly more complicated than with FDEM. Depth penetration of TDEM signals is analyzed by measuring the decay of the secondary magnetic field with time.

Data availability

No data other than the cited papers was used for the research described in the article.

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