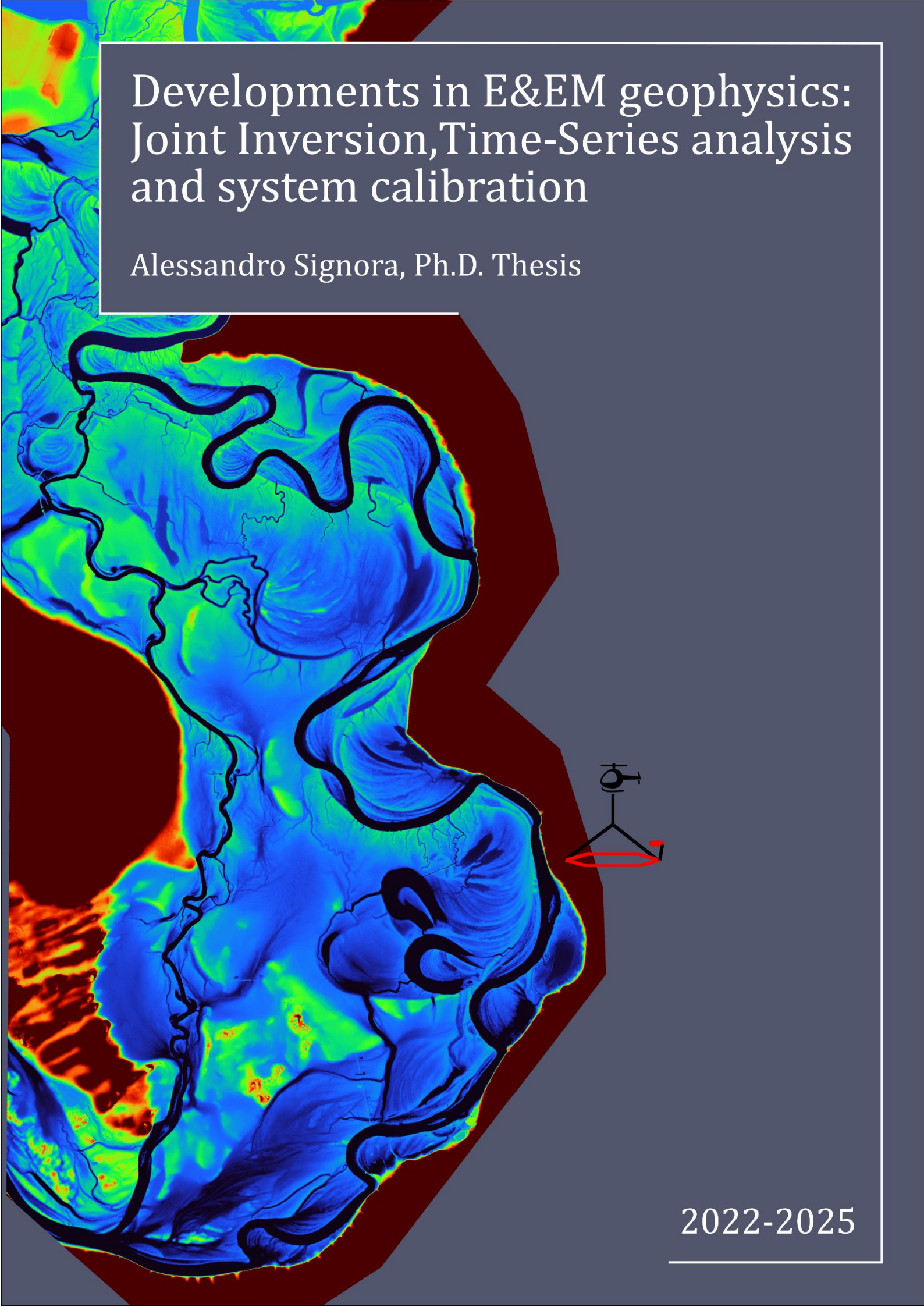




Developments in E&M geophysics: Joint Inversion, Time-Series analysis and system calibration

Alessandro Signora, Ph.D. Thesis

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Alessandro Signora

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Advisor: *Prof. Gianluca FIANDACA*
Co-Advisor: *Prof. Alessandro COMUNIAN*

Thesis Reviewers:

Dr. Burke MINSLEY (USGS)
Prof. Denys GROMBACHER (Aarhus University)

Defence Committee

Prof. Mauro GIUDICI (Università degli Studi di Milano)
Prof. Thomas GÜNTHER (TU Bergakademie Freiberg)
Prof. Denys GROMBACHER (Aarhus University)
Prof. Albert FOLCH (University of Catalonia)

Ph.D. Coordinator: *Prof. Giovanni MUTTONI*



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PREFACE

The research presented in this Ph.D. thesis stems from the execution of the largest Airborne Electromagnetic (AEM) campaign ever conducted in Italy between 2021 and 2023, and the specific challenges that arise from this project. This AEM campaign, financed by A2A, which also co-funds the Ph.D. project, aims to investigate the geological and hydrogeological architecture of a specific region in northern Italy at multiple observational scales—large, medium, and high-detail—to serve as a foundation for long-term hydro-management solutions.

The airborne electromagnetic (AEM) geophysical methodology provides a fundamentally different starting point for addressing water-related issues, offering an entirely new basis for the planning and design of solutions. Its ability to cover wide areas — at regional scale, with several hundreds of line kilometres acquired per day — combined with high data density, enables the detailed characterization of the hydrostratigraphic systems that control groundwater flow and storage at the basin scale. No other geophysical or methods allow for such large-scale and spatially detailed inland analysis and the results are maximized when geological and hydrogeological knowledge is integrated from the acquisition to the modelling and interpretation phases. AEM surveys enable the identification of critical areas where engineering interventions should be focused, while providing a comprehensive understanding of the larger-scale hydrogeological system in which these areas are embedded. This broader perspective supports the development of more effective water management strategies, enhancing the success of applied solutions and possibly minimizing their impact on the overall system.

The first expected research outcome of the Ph.D. is the establishment of the HydroGeosITe within the survey area. This site is designed to act as a bridge between the large-scale geophysical models obtained from the AEM campaign and their lithostratigraphic interpretation. At the same time, the HydroGeosITe is envisioned as a calibration site for AEM systems to support future campaigns. Consequently, another key objective of this Ph.D. research is to advance the state of the art in AEM system calibration procedures, setting a new standard for calibration in Italy.

In the first chapter of this thesis, after a brief introduction to Electrical and Electromagnetic (E&EM) geophysical investigation methods—including their differences, similarities, specific advantages, and historical challenges—the focus shifts to the work conducted to characterize the HydroGeosITe. At this site, an extremely dense E&EM dataset was collected using multiple systems to ensure the broadest range of sensitivities and explored spectral content. Next, the first technical development is introduced: a novel joint inversion approach for E&EM data, which is first applied to model the HydroGeosITe data. This is presented by integrating in the thesis the scientific paper produced from this study (Section 1.2.1). The joint inversion procedure described in the paper demonstrates its ability to retrieve subsurface models with unprecedented resolution, significantly outperforming E&EM independent models. The paper also provides a comprehensive validation through borehole data and a detailed technical analysis of the underlying reasons for the effectiveness of this joint inversion framework.

This joint approach, with its enhanced resolution, has been used to provide a new level of translation from geophysical to geological information. To further strengthen this research objective, at the HydroGeosITe the guidelines for establishing the reference site were derived by extending the high resolution of the joint 2D models into a full 3D volume for the entire site (Section 1.4.1). This enabled a precise definition of the three-dimensional morphology of the geological structures in the subsurface, which was crucial, as the recognition of target lithostratigraphic units in this region can rely on geometrical identification and depositional patterns.

Following this first development and application of the joint inversion approach, it was essential to assess the consistency of its performance across different sites and geological contexts. Still within chapter one, the first additional application is presented, focusing on a follow-up site within the Italian AEM campaign area. This site required a higher resolution than that provided by large-scale AEM models, as it was designated for the construction of a facility for artificial recharge activities (Section 1.4.2). Here too, the results confirmed the superior performance of joint inversion over independent methods, offering a new level of resolution that enables a more informed approach to infrastructure planning. This advancement provides a clearer understanding of the target geological boundaries—in this case, the best aquifer suitable for hosting the injection and the protective aquicludes.

In the second part of the thesis—and of the Ph.D.—the research shifted towards E&EM temporal analysis. These studies range from addressing specific challenges in time-lapse analysis to leveraging the achieved advancements to further refine EM system calibration procedures, one of the original research objectives of the Ph.D.

In particular, the effects of seasonal temperature variations were first examined through a long-term monitoring survey using galvanic data, detailed in the second scientific paper produced during the Ph.D. (Section 2.1.2). In this case, temperature oscillations entirely masked the target anomalies representing the monitored processes, rendering the data unusable. To overcome this issue, a novel inversion scheme was developed to filter out temperature effects by inverting for the ground thermal diffusivity without requiring direct temperature measurements in the ground at the time of data acquisition. As a result, the survey was successfully recovered, producing accurate results with temperature effects removed.

After these findings and the observed strong influence of temperature on resistivity measurements, it was grasped that seasonal temperature variations could similarly impact subsurface models at sites where EM instrument calibrations are conducted, especially since calibrations are not always performed at the same time of year. This realization prompted an initial study on the effect of temperature on EM data (Section 2.1.3), highlighting the risk of misinterpreting thermal variations as hardware differences between instruments during calibration activities.

Still on the topic of temporal analysis, during the Ph.D. research-period abroad at CSIRO, Australia, these studies continued with a focus on an AEM time-lapse dataset collected in the southern part of the country, leading to the third scientific paper of the Ph.D. (Section 2.1.4). The dataset was modelled to investigate the hydrogeological evolution of a hypersaline floodplain and its freshwater recharge. For this purpose, a new time-lapse inversion framework was developed specifically for airborne EM datasets. At the time of writing, this represents, if not the first, one of the earliest attempts in this direction, with the main challenge arising from the lack of established reference methodologies. Therefore, developing a new approach was essential for both AEM data processing and modelling, resulting in successful time-lapse models that provided significant advantages in studying hydrogeological processes over time across the floodplain by accurately depicting its spatial evolution. Moreover, as done in the previous studies, temperature

effects between datasets were carefully verified to ensure they did not influence neither the data nor the models before finalizing the results. In this case, hydrogeological variations were found to be orders of magnitude greater than any potential thermal effects. This was expected, as the different surveys were conducted in similar periods of the year, under comparable thermal conditions, and the AEM system resolution at this site was insufficient to detect minor temperature-driven variations. Thus, we could confidently attribute the observed changes in the geophysical models solely to hydrogeological processes, validated through the calculation of independent hydrogeological parameters within a new validation approach for EM hydro-geophysical models.

Building on these standalone developments and, more specifically, aligning with the Ph.D. research objectives, the development of the multitemporal AEM modelling scheme provides an additional tool for planning future AEM campaigns involving the acquisition of multitemporal datasets, which can now be effectively modelled and interpreted, introducing a new dimension of information.

The last chapter of the thesis summarizes all the research work with an in-depth analysis of temperature effects at EM calibration sites (Section 3.1) and with the application at the CSIRO AEM calibration line of the E&EM joint investigation (Section 3.2), carried out during the concluding phase of the Ph.D. during the period abroad in Australia. The analysis of temperature effects demonstrates that neglected temperature influence in calibration could be even more significant than other system transfer function parameters typically prioritized.

The application at the CSIRO calibration line of the E&EM joint investigation developed at the HydroGeosITe provides the opportunity to further test the approach in a different environment. Even in this completely different geological setting, the joint inversion outperformed independent geophysical model resolution, potentially enhancing the AEM system calibration activities at the site. Furthermore, given the significant interpretational advantages offered by the joint model, the chapter concludes by proposing the conversion of the geophysical models into lithostratigraphic interpretations along the joint section.

The Ph.D. research began with the goal of advancing practices for establishing calibration and reference sites for E&EM systems. This objective has been achieved through extensive

field acquisitions and modelling developments presented in this thesis, as well as additional work extending beyond it. However, when considering the entire research process, it appears that the technical advancements developed to address the initial objectives may have an even greater significance than the original Ph.D. research goals. We believe that the E&EM joint inversion procedure—extensively discussed in this work and still undergoing assessment through its application in other field studies—has the potential to bring a paradigm shift in high-resolution E&EM investigations within the first 500 meters of the subsurface. Furthermore, this high-resolution tool can deliver its full potential not only as a standalone method but also when integrated into AEM campaigns. In large-scale AEM surveys, where regional models provide an initial identification of key areas, the joint inversion can serve as the final refinement tool, offering the highest possible resolution for interpretation or infrastructure planning. The value of this approach also lies in its efficiency, potentially delivering joint models within a few weeks from data acquisition, as well as in its cost-effectiveness relative to the overall budget typical of AEM projects. This makes it feasible to implement multiple refinement points across the survey area, enhancing the spatial resolution in critical zones.

Additionally, the developments proposed for E&EM time series analysis represent another major contribution of this research. Specifically, addressing atmospheric temperature effects on resistivity models during monitoring has raised attention on this often-overlooked effect. At the same time, the results of the AEM time-lapse study open new possibilities for airborne investigations. By introducing a temporal dimension to AEM surveys, the interpretation of complex environmental applications appears enhanced, expanding the capabilities of airborne geophysics beyond traditional single-time models.

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1. JOINT INVERSION OF E&EM DATA AND EM SYSTEM CALIBRATION

Electric and Electromagnetic (E&EM) geophysical techniques aim to describe the subsurface in terms of the distribution of electrical properties. Ideally, as the subsurface at a specific location is unique, these two geophysical methods should depict a consistent and coherent distribution of properties, in agreement with the actual electrical stratigraphy. Nonetheless, even within the same location, galvanic and inductive measurements depict the subsoil features differently. The reasons why exact equivalent models cannot be retrieved arise from various stages of the geophysical process, including theoretical principles, system construction and calibration, as well as data acquisition, processing, and modelling techniques. However, in recent decades, all these geophysical process' stages have advanced significantly, enabling more precise and accurate E&EM measurements able to describe the subsurface with high accuracy. Nevertheless, the challenge of differing models produced by the two techniques has not yet been fully overcome. Two of the main reasons for the discrepancies described are the differing spatial sensitivities to the electrical resistivity (ER) distribution of inductive and galvanic measurements, aside of the specific hardware and software characteristics of the different instruments. Additionally, the actual site conditions may change between the application of one technique and the next. These changes can be mistakenly overlooked, either because they are not recognized or are deemed negligible.

From a practical standpoint, this mismatch issues have been largely addressed through experience and practical solutions, by adjusting, for instance, the choice of survey methods to align with the electrical and spatial characteristics of the target anomalies. To go beyond this type of approach, one of the primary goals of this work is to help bridge the gap between galvanic (E) and time-domain inductive (EM) methods. To achieve so, the key starting point is working with high-quality E&EM data, measured with well-calibrated instruments, with accurately described transfer functions, to be then fully

included into the modelling process. The final aim is to produce E&EM models that can accurately describe both inductive and galvanic measurements, based on the assumption that the two techniques provide only a partial description of the subsurface electrical properties, according to their respective sensitivities and operational frequency-bands. Therefore, the development of a joint modelling procedure, that combines these two data-type, represents the foundation for this work to achieve a more comprehensive modelling. Both inductive and galvanic data are intended to be integrated into a unified inversion framework, including the full of system characteristics in the modelling. In the next sections, an extended presentation of the joint inversion procedure is provided, first covering the theoretical aspects, followed by field application and validation.

1.1 THEORY OF E&EM GEOPHYSICAL METHODS

Electrical and electromagnetic (E&EM) geophysical methods aim at characterizing the subsurface by mapping the distribution of electrical properties. When discussing galvanic and inductive geophysical techniques, it is important to distinguish between them, as they rely on different physical principles for assessing subsurface electrical properties. This leads to significant variations in instrument hardware, software operation, system calibration, and, consequently, modelling strategies.

In the current section, a brief theoretical overview of E&EM methods is provided, together with fundamentals of forward modelling and inversion and calibration procedures. Furthermore, this chapter presents some of the historical challenges in jointly modelling E&EM data, which are considered to stem from the differences in their physical principles. The focus will be on demonstrating that, with an appropriate modelling setup—presented within the first scientific paper of this thesis—it is possible to successfully integrate these datasets into a joint inversion framework. Furthermore, we will present the joint modelling approach as a valuable tool for supporting Airborne EM (AEM) campaigns. Specifically, E&EM joint models can aid the establishment of reference sites for AEM campaigns interpretations and can provide subsoil models with the highest resolution in areas where ground follow-up is needed to achieve a higher level of detail.

1.1.1 GALVANIC SYSTEMS (E)

1.1.1.1 SUBSOIL RESISTIVITY VIA ELECTRICAL MEASUREMENTS

Direct current measurements on the ground aim to describe how easily electrical charges can move through a given material (e.g., porous media) when subjected to an externally induced electric field. In this context, the free charges in a material experience an electromotive force under the influence of this electric field. For now, we treat the subsurface as the equivalent of a purely resistive electrical circuit, assuming that capacitive and inductive effects are negligible. Within these assumptions the transport of charge within the medium is related to conduction via the ions dissolved within the pore fluid filling the interconnected pore space, conduction via the ions at the interface between fluid and rock matrix and, possibly, semi-conductor conduction of p-n pairs and electron conduction in metal ores. In this thesis we concentrate only on the first two mechanisms, the most relevant in geological and hydrogeological characterizations not linked to mineral exploration. The current density follows Ohm's law:

$$\vec{j} = \sigma \cdot \vec{E} = \frac{1}{\rho} \cdot \vec{E} \quad (1)$$

Where ρ represent the electrical resistivity (Ohm·m), reciprocal of electrical conductivity σ (S/m), which in this thesis are treated as scalars, i.e., neglecting anisotropy.

In the case of a current-carrying wire, the potential difference between the two ends of the wire is the line integral of the electric field along the wire changed of sign:

$$V = - \int \vec{E} \cdot d\vec{l} = - \int \rho \cdot \vec{j} \cdot d\vec{l} \quad (2)$$

which gives, for an electrically homogeneous wire with constant section, and assuming a uniform electric field across it:

$$V = \rho \cdot I \cdot \frac{l}{A} \quad (3)$$

where we used the relation $I = \vec{j} \cdot \vec{A}$ that define the total current I as the flux of the current density $\vec{j}$ through a section $\vec{A}$.

Reversing Eq. (3), we obtain the classic formula for the resistivity of a wire:

$$\rho = \frac{V}{I} \cdot \frac{A}{l} = \frac{V}{I} \cdot k \quad (4)$$

where $k = \frac{A}{l}$ is the geometrical factor of the wire, i.e. the proportionality factor between resistivity and resistance.

Now considering the practical case of geophysical direct current measurements in a subsurface medium that can be approximated as a half-space in contact with air, we redefine the cross-sectional area A in Eq. (4) as the surface area of a hemisphere. In the context of a quadrupole measurement setup, where electrodes A and B generate the electric field and electrodes M and N measure the resulting potential, we can express the resistivity as follows:

$$\rho = \frac{V_{MN}}{I_{AB}} \cdot \frac{2\pi}{\left(\frac{1}{|\overline{AM}|} - \frac{1}{|\overline{AN}|} - \frac{1}{|\overline{BM}|} + \frac{1}{|\overline{BN}|} \right)} = \frac{V_{MN}}{I_{AB}} \cdot k \quad (5)$$

Where $\overline{AM}$, $\overline{AN}$, $\overline{BM}$, and $\overline{BN}$ represent the distances between the electrodes in the quadrupole configuration, V_{MN} is the voltage measured by the potential dipole, and I_{AB} is the current injected through the current dipole and k is the geometrical factor for a quadrupolar measurement on a half-space. Eq. (5) represents the resistivity of the medium when the subsurface is homogeneous and isotropic, and assuming point-like electrodes and flat topography. When all these conditions are not met, Eq. (5) represents the apparent resistivity value ρ_{app} , which is a positive homogeneous function of first degree of the true resistivity distribution $\rho(x, y, z)$, so that for any positive number (Seigel, 1959):

$$\rho_{app}(\lambda \cdot \rho(x, y, z)) = \lambda \cdot \rho_{app}(\rho(x, y, z)) \quad (6)$$

Computing the apparent resistivity for a given resistivity distribution means computing the galvanic forward mapping, which is set up putting together Ohm's law, the relation between the electric field and the electric potential and the law of charge conservation.

We start expressing Ohm's law in terms of electric potential as:

$$\vec{J} = -\sigma \cdot \nabla V \quad (7)$$

where we used the relation $\vec{E} = -\nabla V$ between electric field and electric potential. This leads to a direct relationship between the current density and the electric potential through electrical resistivity. According to the law of charge conservation, the flux of the current density through a closed surface is equal to the time derivative of the charge contained in the volume enclosed by the surface, changed of sign. Making use of the divergence theorem, the charge conservation takes the differential form:

$$\nabla \cdot \vec{J} = -\frac{\partial \rho_q}{\partial t} \quad (8)$$

where ρ_q represents the charge density. Putting together Eq. (7) and Eq. (8) we obtain the classic Poisson's equation for galvanic data:

$$\nabla \cdot (\sigma \cdot \nabla V) = -\frac{\partial \rho_q}{\partial t} = -I \cdot \delta(x, y, z) \quad (9)$$

where in the last equality the source term is expressed in terms of the current I injected in the position $\delta(x, y, z)$.

1.1.1.2 Subsoil Chargeability via Electrical Measurements

The electrical conductivity of the subsoil is a physical property composed of both a real part, which represents the electromigration process as described in the previous section, and an imaginary part, which accounts for the fact that the geological medium can act as a capacitor, temporarily and reversibly storing a certain amount of charge depending on its intrinsic characteristics. Now, Ohm's law can be expressed in terms of complex resistivity, where it is represented as a function of both real and imaginary components:

$$\vec{J} = \frac{1}{\rho^*} \vec{E} = \sigma^* \vec{E} \quad (10)$$

Eq. (10) is valid in frequency domain, because in time domain the current density is the convolution of time-varying electric field and time-varying electric conductivity.

Depending on the frequency at which the measurements are conducted, different capacitive mechanisms are investigated (Binley and Slater, 2020). It is generally considered that at low frequencies (freq. $<10^3$ Hz), which is the typical range for field galvanic and induced polarization (IP) surveys, two main polarization mechanisms occur:

i) diffusion-controlled polarization at the interface between rock matrix and fluid and *ii)* electrode polarization in presence of metallic minerals. In the frequency range between 10^2 and 10^8 Hz, the Maxwell-Wagner mechanism becomes significant, explaining polarization effects due to permittivity discontinuities at the interfaces between different phases in the porous media (e.g., solid, liquid, and gas phases). At very high frequencies (freq. $>10^8$ Hz), dipolar polarization of water molecules becomes the dominant factor in capacitive measurements. At the interface between rock matrix and fluid, together with surface polarization effects, surface conduction occurs. At low frequencies, and in absence of electrode polarization, the total complex conductivity is usually expressed as:

$$\sigma^* = \sigma_{bulk} + \sigma'_{surf} + \sigma''_{surf} \quad (11)$$

where the bulk conductivity depends on the fluid conductivity, fluid saturation and formation factor through Archie's law (Archie, 1942). For media saturated with water Eq. (11) becomes:

$$\sigma^* = \frac{\sigma_w}{F} + \sigma'_{surf} + \sigma''_{surf} \quad (12)$$

where σ_w represents the water conductivity and F is the formation factor.

Empirical studies (Weller et al., 2013) have shown that surface polarization and surface conduction are proportional, being both dependent on the extent of surface area per unit volume:

$$\sigma''_{surf} = l \cdot \sigma'_{surf} \quad (13)$$

where the proportionality factor $l = 0.042 \pm 0.022$ was obtained from a database of 63 samples of sandstone and unconsolidated sediments, covering nine independent investigations, using multisalinity resistivity measurements. Eq. (13) means that the charge storage is relatively small compared to the electromigration component, which is the sum of surface and bulk conduction. In these cases, the phase of complex conductivity can be approximated with the ratio between imaginary and real conductivity:

$$\varphi = \tan^{-1} \left[\frac{\sigma''}{\sigma'} \right] = \tan^{-1} \left[\frac{\sigma''_{surf}}{\sigma'_{surf} + \frac{\sigma_w}{F}} \right] \cong \frac{\sigma''_{surf}}{\sigma'_{surf} + \frac{\sigma_w}{F}} \quad (14)$$

Eq. (13) first and (14) then, imply that in the absence of electrode polarization, the maximum phase of the complex conductivity is limited to $10^3 \cdot l \text{ mrad}$. That condition is reached when the bulk conductivity tends to zero. On the contrary, high bulk conductivity, for instance in presence of high water conductivity, gives very small IP effects, because φ tends to zero ($\sigma''_{surf} \propto \sqrt{\sigma_w}$, e.g., Weller et al., 2015).

The complex conductivity of Eq. (12) is dispersive: typically, the modulus increases with frequency, while the phase shows either a flat spectrum, or a spectrum with one or more maxima. While in the laboratory the spectra are generally analyzed through Debye decomposition, in field applications two simple parameterizations are usually used: the Constant Phase Angle (CPA) model (e.g., Van Voorhis et al., 1973; Johansson et al., 2015) and the Cole-Cole model (Cole and Cole, 1941; Pelton et al., 1978). The Cole-Cole model can be expressed either as complex conductivity or complex resistivity, in terms of four parameters, as follows:

$$\sigma^*(\omega) = \sigma_0 \cdot \left(1 + \frac{m_0}{1 - m_0} \cdot \left(1 - \frac{1}{1 + (i\omega\tau_\sigma)^C} \right) \right) \quad (15)$$

$$\rho^*(\omega) = \rho_0 \cdot \left(1 - m_0 \cdot \left(1 - \frac{1}{1 + (i\omega\tau_\rho)^C} \right) \right) \quad (16)$$

where σ_0 and $\rho_0 = \frac{1}{\sigma_0}$ are the DC conductivity and resistivity, respectively; m_0 represents the intrinsic chargeability; τ_σ and τ_ρ are the relaxation times and C is the frequency exponent. In particular, τ_σ represents the inverse of the angular frequency ω at which the imaginary conductivity $\sigma''(\omega)$ reaches its maximum, while τ_ρ represents the inverse of the angular frequency ω at which the imaginary conductivity $\rho''(\omega)$ reaches its minimum. Eq. (15) and Eq. (16) represent one the inverse of the other when $\tau_\sigma = \tau_\rho \cdot (1 - m_0)^{\frac{1}{C}}$. The frequency exponent C determines the sharpness/flatness of the spectrum: $C = 1$ represents a Debye relaxation; $C = 0.5$ gives the Warburg model; in the limit of $C \rightarrow 0$, the Cole-Cole formula tends to the CPA one.

In this thesis, a re-parameterization of the Cole-Cole formula is used for modelling the polarization, i.e., the Maximum Phase Angle (MPA) model proposed by Fiandaca et al., (2018). This model expresses the Cole-Cole formula using, instead of the classic parameters m_0 and τ_σ (or τ_ρ), the parameters φ_{max} and τ_φ . The relaxation time τ_φ represents the inverse of the angular frequency ω at which the phase of the Cole-Cole model $\varphi(\omega)$ reaches its maximum, while φ_{max} is the maximum itself. The reason for employing the MPA parameterization, instead of the classic Cole-Cole formula, is that much weaker correlations exist between the MPA parameters instead of the classic ones, hence improving considerably the inversion results (Fiandaca et al., 2018).

The IP phenomenon is usually investigated in the field using galvanic measurements, either in frequency domain or in time domain. In this thesis, time-domain measurements are used. The time-domain IP acquisition can be carried out either in 50% duty-cycle or in 100% duty cycle (Olsson et al., 2015). In 50% duty cycle acquisitions, the IP measurement is carried out during the off-time, while in 100% duty cycle the IP measurement is carried in the on-time, in the potential ramp-up. Olsson et al., (2015) proposed a decay-like definition of the 100% duty cycle transients, obtained as:

$$M_i = \frac{V_{DC} - V_{IP_i}}{V_{DC}} \cdot \frac{n}{2n - 1} \cdot 1000 \quad (17)$$

where M_i represent the data chargeability value (mV/V) obtained for the i^{th} integration time interval, V_{DC} is the direct current voltage, and V_{IP_i} is the voltage measurements of the IP decay in the i^{th} time interval and n represents the number of stacking pulses.

The normalization of $V_{DC} - V_{IP_i}$ by the DC voltage V_{DC} (or the equivalent normalization of V_{IP_i} by V_{DC} in 50% duty cycle measurements) allows to disentangle chargeability effects and conduction effects, making the data-space chargeability M an analogous of the model-space intrinsic chargeability m_0 . However, it is worth noting that the signal-to-noise ratio of the IP data depends on the $V_{DC} - V_{IP_i}$ signal level. Consequently, following Olsson et al., (2015), the standard deviation on IP data is computed adding to a uniform relative uncertainty a signal-level dependent uncertainty, computed as:

$$\sigma_{M_i} = \frac{V_{Noise}}{M_i \cdot V_{DC}} \cdot \frac{1}{\sqrt{Stack_Size}} \cdot \frac{1}{\sqrt{Gate_Width_i/10}} \quad (18)$$

where V_{Noise} represents the noise threshold specific to the site and to the instrument used, for a nominal integration time of 10 ms and stack 1, M_i is chargeability as defined in Eq. (17), $Stack_Size$ refers the number of repeated measurements for the quadrupole, and $Gate_Width_i$ is the total time window for the i -th gate (in milliseconds).

The forward computations for time domain IP data are obtained solving Poisson's equation (Eq. (9)) in 2D in frequency domain with a dispersive complex conductivity and transforming the results in time domain through a Hankel transform, following the approach developed in Fiandaca et al., (2013).

1.1.1.3 Calibration of Galvanic systems

Typically, electrical investigation instruments, such as geo-resistivity meters, require fewer calibration stages compared to inductive instruments. In these cases, hardware calibration is primarily carried out in the lab, measuring voltages and currents on matrices of resistors with known values. Once completed, these calibrations are generally considered stable and consistent over extended periods. Therefore, the calibration of galvanic system will not be the central focus in the present work.

1.1.2 INDUCTIVE SYSTEMS (EM)

1.1.2.1 SUBSOIL RESISTIVITY (AND CHARGEABILITY) VIA EM MEASUREMENTS

Inductive or ElectroMagnetic (EM) measurements aim to describe the subsoil in terms of electrical properties distribution, similarly to galvanic measurements, but involve different physical principles for investigating these properties. In Transient EM (TEM) measurements, continuous current is typically established within a transmitter loop that is not in galvanic contact with the ground, generating a primary magnetic field. The current is then rapidly turned off, causing a rapid decay of the primary magnetic field, which induces an ElectroMotive Force (EMF) in the subsoil, in accordance with Faraday's law of induction:

$$\oint_C \mathbf{E} \cdot d\mathbf{l} = -\frac{d}{dt} \oint_S \mathbf{B} \cdot d\mathbf{A} \quad (19)$$

$$\nabla \times E = - \frac{dB}{dt} \quad (20)$$

where Eq. (19) and Eq. (20) represent the integral and the differential form of Faraday's law.

The irrotational electric field generated by the time-decreasing flux of the magnetic field of the transmitter creates in the subsurface eddy currents that are dissipated because of ohmic losses. The secondary magnetic field generated by the eddy currents is the target signal of the TEM method and the entire measurement process takes a few milliseconds, during which the secondary magnetic field is measured after the current in the transmitter loop is completely turned off.

In this study the forward calculations are carried out in 1D, with electrical properties that vary only vertically. The computations are carried out in the frequency domain by following the method outlined in Ward and Hohmann (1988), as a superposition of the magnetic field generated by horizontal electric dipoles along the transmitter loop, and then transformed in time domain through a Hankel transform, as presented in Johansen and Sørensen, (1979). In particular, the magnetic field in frequency domain is:

$$B_{z,FD}(\sigma, \mathbf{h}, \omega, x, y, z) = \oint_{Tx \text{ loop}} dB_{z,FD} \quad (21)$$

where $\sigma = \{\sigma_1, \dots, \sigma_N\}$ and $\mathbf{h} = \{h_1, \dots, h_{N-1}\}$ represent the electric conductivity and the layer thicknesses of a N-layered 1D model, ω is the angular frequency, x, y, z indicate the position of the receiver and $dB_{z,FD}$ is the contribution of the infinitesimal loop piece of length ds , expressed as:

$$dB_{z,FD}(\sigma, \mathbf{h}, \omega, x_*, y_*, z_*) = \frac{I \cdot ds}{4\pi} \cdot \frac{y_*}{\rho_*} \int_0^\infty (1 + r_{TE}) e^{\mu_0 z_*} \cdot \frac{\lambda^2}{\mu_0} \cdot J_1 \cdot (\lambda \cdot \rho_*) \cdot d\lambda \quad (22)$$

where x_*, y_*, z_* are the receiver coordinates in the reference system that sees the infinitesimal loop piece as oriented in the x direction and centered at its origin, J_1 represents the Bessel function of order 1, $\rho_* = \sqrt{x_*^2 + y_*^2}$ is the distance between the receiver and the segment origin, I is the current in the loop, $u_0 = (\lambda^2 - \omega^2 \mu_0 \epsilon_0)^{1/2}$ and r_{TE}

represents the reflection coefficient of the electric field transverse to the z-axis, defined as:

$$r_{TE} = \frac{Y_0 - \hat{Y}_1}{Y_0 + \hat{Y}_1} \quad (23)$$

Where Y_0 and $\hat{Y}_1$ are respectively the admittance of the free space and the surface admittance computed as in Ward and Hohmann (1988).

The frequency domain kernel of Eq. (21) is multiplied with the frequency characteristics of the receiver (in terms of both coil and instrumental filters) and the impulse response obtained through the time-transformation is then convolved with the current waveform, following Fitterman and Anderson, (1987).

In EM measurements, several factors can contribute to increased noise levels, including spherics-induced noise, which manifests as impulsive and highly variable signals; VLF noise (3-30 kHz); interference from power lines (50 Hz); internal electronic noise from the system; motion-induced noise if the EM measurement is not conducted in a static setup; coupling, either capacitive or galvanic, with metallic infrastructures inductively coupled with the transmitter and receiver. Synchronous detection (i.e. acquisition synchronized with the powerline frequency), stacking and signal gating help in reducing random and harmonic noise. The inductive coupling is treated by culling coupled data out in the processing phase, before inversion.

1.1.2.2 Calibration of EM systems

The calibration of Time-Domain inductive systems requires more steps compared to the galvanic ones. After the characterization of the system response, typically with in-lab procedures, the field calibration plays a crucial role in ensuring the EM systems respond consistently to a standardized inductive response. This is typically achieved by establishing a reference site (e.g., Foged et al., 2013; Sapia et al., 2015), where the subsurface electrical model is thoroughly characterized, so that a corresponding forward response can be computed for any EM system. Ideally, such a site would exhibit favorable resistivity distributions (e.g., highly resistive areas for EM system calibration) and have no significant change of the electrical properties over time.

The reference response is calculated employing the complete description of the inductive system characteristics (e.g., Tx waveform, transmitter-receiver timing, receiver filter frequencies, front-gate times, etc.) provided by the in-lab analysis. This description defines the so-called system transfer function of a specific instruments, which inclusion in the forward response computation has proven crucial for accuracy (Christiansen et al., 2011). Therefore, in the context of EM calibrations, an inaccurate description of the system transfer function can lead to significant discrepancies in the computed forward response, hindering precise calibration.

From a practical perspective, when calibration is performed in the data space, the intent is to eliminate any differences between the reference and measured responses. This overlap is achieved by adjusting the on-field measured signal, of the instrument being calibrated, until it is considered acceptably close to the reference response, typically within the error-bars or a specific misfit range. Two types of adjustments are generally applied for calibrating the signals (Figure 1): a time-shift, where the gate times are moved forward or backward, and a level-shift, where the entire transient is scaled by a multiplying factor. These adjustments are designed to modify the signal in terms of gate time and amplitude that are related to specific electronic components of the transmitter and receiver systems. These components are in fact difficult to be fully characterized in the laboratory and are more effectively calibrated through field procedures. Additionally, when calibrating an Airborne EM system, multiple flight heights are typically measured. The calibration of all data measured at different heights must be accomplished using the same time and level shifts. This ensures that only electronic differences are compensated for, confirming that the EM coils sense the subsoil model without bias at different altitudes, although accounting for signal loss at higher clearances.

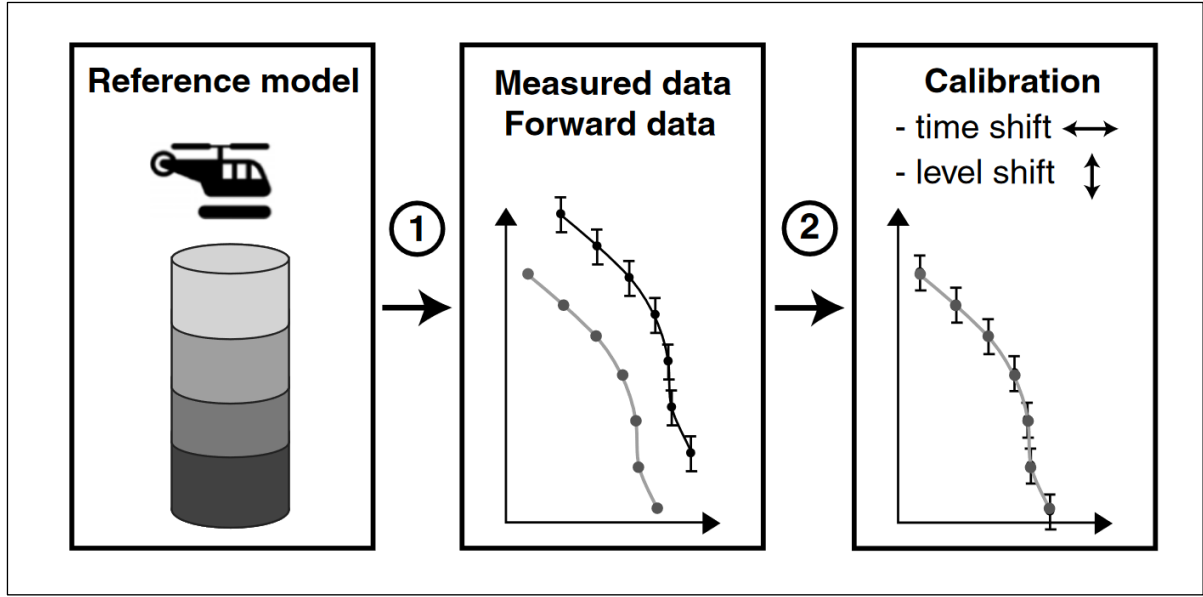


Figure 1: Typical calibration scheme for EM systems that leverages the differences between on-field and reference responses by applying time and level shifts to the measured signal. Figure extracted by Foged et al. (2013).

1.1.3 FUNDAMENTAL OF E&EM INVERSIONS

The application of inversion procedures, to the study of electrical properties distribution in the subsoil, aims to retrieve the most accurate electrical model from the measured data. In electrical and electromagnetic inversions, the relationship between data and model parameters is inherently non-linear. To address this, a linearization of the problem is performed using a Taylor series expansion of the non-linear function, which is then solved iteratively. The model update between subsequent iterations for a linearized, discretized and regularized inversion process is defined by the following equation:

$$m_{n+1} = m_n + \left\{ \left[G^T \cdot C_{obs}^{-1} \cdot G + R^T \cdot C_R^{-1} \cdot R + C_{pr}^{-1} + \lambda \cdot I \right]^{-1} \cdot G^T C_{obs}^{-1} \cdot (d_{obs} - g(m_n)) + R^T C_R^{-1} \cdot (-R \cdot m_n) + C_{pr}^{-1} (m_{pr} - m_n) \right\} \quad (24)$$

where the updated model m_{n+1} is derived by perturbing the previous one m_n , with the aim of iteratively minimizing the difference between the observed data and the predicted data (forward response), as well as the model regularization, following the approach of Auken et al., (2014a).

In the model update equation, the matrix G is the Jacobian, which represents the sensitivity of the predicted data to changes in the model parameter and is defined as:

$$G = \begin{bmatrix} \frac{\partial d_1}{\partial m_1} & \dots & \frac{\partial d_1}{\partial m_N} \\ \vdots & \ddots & \vdots \\ \frac{\partial d_M}{\partial m_1} & \dots & \frac{\partial d_M}{\partial m_N} \end{bmatrix} \quad (25)$$

Where M represents the number of data points d , and N represents the number of model parameters m .

The square matrix C_{obs} is the inverse of the data covariance matrix, which accounts for the measurement uncertainties:

$$C_{obs} = \begin{bmatrix} \varepsilon_1^2 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \varepsilon_M^2 \end{bmatrix} \quad (26)$$

where the diagonal values ($\varepsilon_{ii}=\sigma_i^2$) represent the variance for the i -th data.

The matrices R and C_R ensure the smoothness of the solution, imposing vertical and horizontal constraints. Each row of the R matrix represents a constraint, which penalizes the difference between the two model parameters:

$$R = \begin{bmatrix} -1 & 1 & 0 & 0 & \dots & 0 \\ 0 & -1 & 1 & 0 & \dots & 0 \\ 0 & 0 & -1 & 1 & \ddots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & 0 & \dots & -1 & 1 \end{bmatrix} \quad (27)$$

The square matrix C_R represents the covariance matrix of the roughness constraints, which control the constraint strength.

The term C_{pr} represents the covariance matrix of possible prior information included in the inversion process. This allows the expression of confidence in the prior information, effectively controlling how closely the updated model sticks to the prior values in the relevant parts of the model. The terms λ and I represent the inversion damping factor, as defined by (Auken et al., 2015), and the identity matrix, respectively. The damping factor

controls the magnitude of the model update, and tunes the Levenberg-Marquardt approach: when λ is small, the weight of $\lambda \cdot I$ become negligible, keeping the inversion process within the Gauss-Newton solution framework (Eq. (28)); as λ is increased, its influence becomes dominant in computing the model update, shifting the solution towards the gradient descent domain (Eq. (29)).

$$m_{n+1} = m_n + \left\{ \left[G^T \cdot C_{obs}^{-1} \cdot G + R^T \cdot C_R^{-1} \cdot R + C_{pr}^{-1} \right]^{-1} \cdot G^T C_{obs}^{-1} \cdot (d_{obs} - g(m_n)) + R^T C_R^{-1} \cdot (-R \cdot m_n) + C_{pr}^{-1} (m_{pr} - m_n) \right\} \quad (28)$$

$$m_{n+1} = m_n + \left\{ [\lambda \cdot I]^{-1} \cdot G^T C_{obs}^{-1} \cdot (d_{obs} - g(m_n)) + R^T C_R^{-1} \cdot (-R \cdot m_n) + C_{pr}^{-1} (m_{pr} - m_n) \right\} \quad (29)$$

The objective function Q minimized by Eq. (24) can be expressed as:

$$Q = \sqrt{\left[\frac{1}{N_d + N_R + N_{pr}} \cdot \sum_{i=1}^{N_d} \frac{(d_{obs,i} - d_{fwr,i})^2}{\sigma_{d_i}^2} + \sum_{k=1}^{N_R} \frac{(m_{i(k)} - m_{j(k)})^2}{\sigma_{R_k}^2} + \sum_{i=1}^{N_{pr}} \frac{(m_i - m_{pr_i})^2}{\sigma_{pr_i}^2} \right]} \quad (30)$$

Where N_d , N_R , and N_{pr} represent the number of observed data points, the number of enforced constraints, and the number of prior elements, respectively. $d_{obs,i}$ is the i -th measured data point, and $d_{fwr,i}$ is the corresponding value estimated by the forward response. The terms $\sigma_{d,i}^2$, $\sigma_{R,k}^2$, and $\sigma_{pr,i}^2$ represent the variances for the data, roughness constraints and prior constraints, respectively.

The objective function seeks to minimize the total misfit, which is derived from the weighted sum of these three terms, accounting for their respective uncertainties and quantities. The function serves also as a tool to stop the iterative inversion process when the variation in misfit between consecutive iterations falls below a chosen threshold (e.g., a change of less than 1% in the total misfit value), ideally converging towards a value of 1, where the predicted responses perfectly match the measured data.

1.1.4 HISTORICAL PROBLEMS OF COMPATIBILITY BETWEEN E&EM SYSTEMS

As discussed in the previous sections, inductive and galvanic methods for subsurface investigation are based on different physical principles, resulting in varying sensitivities to the resistivity distribution of the subsoil. Consequently, when different E&EM methods are applied to the same location or subsurface section, the inversion models they produce often depict electrical anomalies differently. For decades, various authors (e.g., Jupp and Vozoff, 1977; Raiche et al., 1985; Sandberg, 1993) have explored the feasibility of joint inversion, although the term is often used to refer to different concepts in the literature, trying to reconcile the two methods within a unique model. In Section 1.2.1, we narrow the joint inversion definition focusing specifically on a specific category of inversion strategies that tries to combine galvanic and inductive measurements within a unified framework whose details will be presented later in the text.

Since both E&EM methodologies aim to describe the subsoil in terms of electrical properties, it might be mistakenly assumed that the models derived from each method represent the exact same physical subsoil properties, despite their differences in sensitivity. However, reconciling discrepancies between E&EM data in practice has been claimed to be more complex than merely accounting for these sensitivity differences.

For instance, Christensen, (2000) highlights the issue that E&EM measurements are sensitive to different components of subsurface electrical resistivity. Inductive measurements primarily detect the horizontal component of electrical resistivity, as eddy-currents generated by variations in the primary magnetic field induce horizontal current flow in the ground. In contrast, galvanic measurements are more sensitive to the geometric mean of both the horizontal and vertical components of electrical resistivity. In this context, the author proposes introducing the "coefficient of anisotropy" to reconcile the two methods within a joint inversion. This coefficient is suggested as a crucial parameter for accurately estimating subsurface properties, and it is not only considered relevant but a necessary condition for successfully performing the joint modeling.

Meju (2005), introduce the concept of "electrical static shift," where the author corrects distortions in galvanic sounding curves using inductive measurements before integrating the different datasets into a joint inversion. The goal of this approach is to ensure first

consistency, completeness, and compatibility between E&EM data, allowing for a more accurate and unified dataset, to ultimately enable the joint inversion. The author references the work of Christensen (2000) and Auken et al., (2001) , noting that while Christensen, (2000) highlights the necessity of using the coefficient of anisotropy for joint inversion, Auken et al. (2001) argues that it is not required when using a mutual constraint inversion approach. However, neither of these studies incorporates a static shift correction of the data. Nevertheless, Meju (2005) concludes his work by incorporating the static shift correction as an inversion parameter. He states that, in the context of the field case study, it was impossible to derive a satisfactory and geologically meaningful joint 1D model that combined DC and TEM data without first correcting the affected electrical data for the static shift.

Christiansen et al., (2007) present a study where a joint inversion of inductive and galvanic data is performed without applying data corrections or compensations. They first highlight the different sensitivities of the two techniques and the fact that they sample distinct subsurface volumes. Their inversion strategy involves initially generating individual E&EM models using an LCI architecture (Auken et al., 2008), followed by linking these independent models through a Mutually Constrained Inversion (MCI). This approach enforces mutual constraints within a simultaneous inversion process governed by a unified objective function, producing two final models. The authors report improved resolution in both the shallow and deep portions of the model, which could not be achieved by inverting the datasets separately. They argue that forcing the different datasets to fit a single model in a joint inversion is not feasible from a data-fitting (misfit) perspective. Instead, the mutually constrained inversion allows for soft constraints between models, enabling the datasets to fit slightly different models while still benefiting from the joint approach.

In a similar attempt, Christensen (2022) produced MCI models by jointly inverting towed galvanic data and Airborne EM data, using the results as prior models for a final, separate inversion of the individual datasets. The study recalls the effects of anisotropy on the data and the necessity of addressing the scale and resolution discrepancies between the two measurement systems. To tackle the scale differences, the author applied down-weighting to the galvanic data below a certain depth within the inversion framework, creating a form

of compensation towards the inductive data. However, regarding the anisotropy issue, no correction was applied.

1.2 NEW E&EM JOINT INVERSION PROCEDURE

In this section, we aim to reconcile E&EM methods by proposing a novel joint inversion scheme, within a unified inversion framework, and without applying any data compensation or correction beyond standard data processing with culling of noisy data. The main idea is that the challenges described in the previous sections in jointly inverting E&EM data sets are not primarily due to data incompatibility nor to anisotropy of electrical properties. Instead, they can be addressed by a joint modelling that accounts for all measuring system complexities, fully incorporating their characteristic (system transfer functions), accounting for the specific conditions in which the measurements are performed and including data uncertainties. Therefore, this approach must be featured by an inversion framework capable of simultaneously handling different forward computations with multiple governing equations solution and mesh discretization and regularization. The joint inversion scheme proposed in this work outcomes a single model attempting to merge the different sensitivities of E&EM techniques, to turn their differing characteristics into an exploration advantage rather than a limitation.

Another key aspect deemed for performing the joint inversion is the inclusion of the capacitive properties of the ground, thereby removing an important layer of approximation that would otherwise oversimplify reality (see section 1.1.1.2). Specifically, in the context of E&EM techniques, many authors (e.g., Marchant et al., 2014; Kang and Oldenburg, 2016; Viezzoli and Manca, 2020; Dauti et al., 2022; Fiandaca et al., 2022) state that the polarization characteristics of the ground not only significantly affect galvanic measurements but also have a substantial impact on inductive measurements (Figure 2). Failing to account for these effects has been proven by these authors to lead to erroneous modeling results (Viezzoli, 2024).

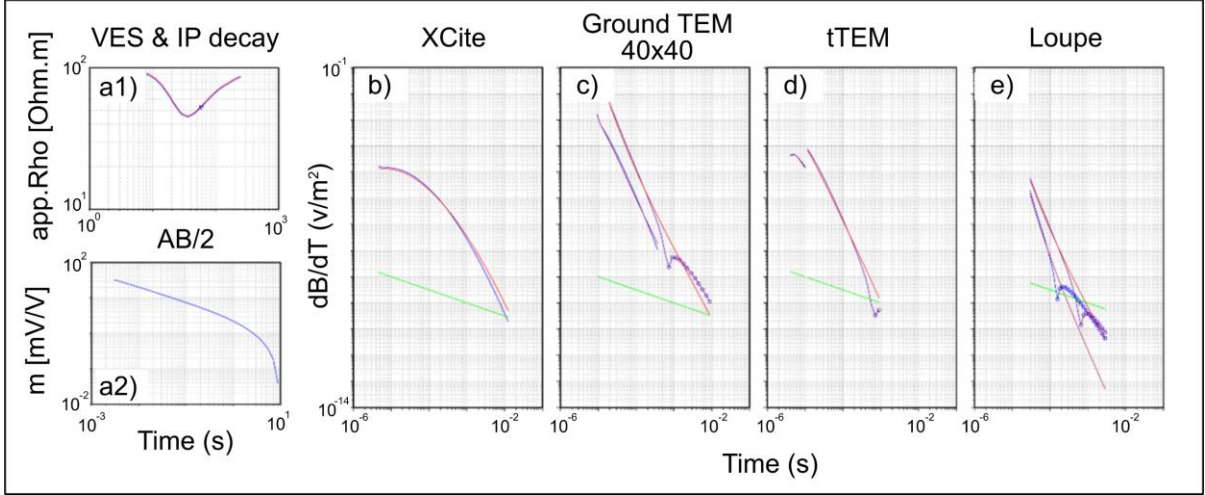


Figure 2: Synthetic simulation of induced polarization effects on galvanic data (panels a1 and a2) and on inductive data from different EM systems, including airborne data (panel b), ground TEM data (panel c), towed ground TEM data (panel d), and backpack-mounted ground TEM data (panel e). Image modified from Fiandaca et al., (2022).

The joint inversion proposed in this work is conducted with EEMverter (Fiandaca et al., 2024), an inversion suite designed for accurate modeling of system characteristics of both inductive and galvanic data. Within a unified inversion framework, we intend to simultaneously model inductive, galvanic, and galvanic full-decay induced polarization data. A key aspect for doing so within EEMverter is the possibility to define different forward meshes for modelling the specific data types included in the dataspace. This is achieved by disentangling the forward and model meshes (Figure 3), to tailor then each mesh to compute the specific forward response.

The multiple forward meshes are linked to a unique model mesh, where the inversion parameters are defined, by interpolating model mesh parameters onto the forward mesh discretization, which can range from 1D to 3D (see Christensen et al., 2017; Madsen et al., 2020; Zhang et al., 2021). More specifically, the interpolation of a model parameter M , defined on the model mesh nodes into the values m_i , at the subdivisions of the i -th forward mesh, is expressed through a matrix multiplication. Here, the matrix F_i contains the interpolation weights, which depend solely on the distances between the model mesh nodes and the subdivisions of the i -th forward mesh (Eq. (38)). EEMverter enables also the possibility of defining different model meshes for different parameters, allowing specific discretization and regularization for each parameter.

Another important flexibility aspect introduced by EEMverter is the possibility to define multiple inversion cycles. Within each inversion cycle, a complete inversion process reaching convergence is expected (Figure 4). When multiple inversion cycles are set, they are performed sequentially, with each cycle using the final model of the previous cycle as its starting model. In each new cycle, different datasets, inversion parameters, constraints, norms, and other settings can be redefined to finely tune the model space exploration. This multiple cycle strategy could help, for instance, balancing the data space whenever the data distribution is not even across plane-space and depth, helping mitigate the effect of potential dominant sensitivity biases in the inversion.

The next section provides a comprehensive description of this novel E&EM joint inversion scheme, including its direct application to a field study characterized by extensive multisystem geophysical data coverage. This joint inversion approach does not apply compensation between inductive and galvanic data, and its results are validated through borehole geophysical ground-truthing.

One of the main focuses in assessing the joint inversion is to study and test its stability and consistency. Repeatability is demonstrated in the real case study in Section 1.2.1.4, where we assessed consistency by performing the joint inversion across multiple, spatially close profiles. Beyond this field study, we also conducted tests introducing perturbations to the inversion process, such as strongly varying the starting model or altering the sequence and order of inversion cycles. These modifications led to only minor variations in the final model, minor enough to not impact the interpretation. We attribute this minimal effect to the fundamentally strong data-driven nature of this approach, achieved through purposeful planning of field measurements to ensure a high density of both inductive and galvanic data points, balanced in quantity and evenly distributed across the study area (a priority also emphasized by Christensen, 2022). Alongside high data-density to allow the inversion process to be data-driven, data-quality is critical. Therefore, measurements must be acquired using well-calibrated instruments with clear transfer functions, to finally integrate into the joint modeling their uncertainty analysis.

1.2.1 PAPER - JOINT INVERSION OF ELECTRICAL AND ELECTROMAGNETIC DATA INCLUDING INDUCED POLARIZATION: SIGNIFICANT RESOLUTION IMPROVEMENTS HONORING BOTH DATA TYPES

Signora A.¹, Galli S.¹, Dauti F.¹, Fiandaca G.¹

¹*The EEM Team for Hydro & Exploration, Department of Earth Sciences, University of Milan (Italy). E-mail: alessandro.signora@unimi.it*

*** The manuscript presented in this section is under submission to the Geophysical Journal International and is reported in its complete form. ***

1.2.1.1 SUMMARY

In this work, we present a Electrical and ElectroMagnetic (E&EM) joint inversion scheme based on the full integration of system transfer functions, disentangling of forward and model meshes, and the inclusion of the Induced Polarization (IP) effects. The resulting joint models improved resolution significantly and revealed entirely new resistivity structures undetected in the independent models.

The joint inversion of E&EM data is traditionally deemed unfeasible without data compensation due to the differing sensitivities of the two methods to subsoil resistivity distribution and anisotropy. In this work, we surpass this notion by presenting a joint modelling approach that relies on purposeful data acquisition, rigorous processing, and a modelling framework that fully accounts for the complexity of the problem.

The joint inversion framework performs 1D and 2D modelling for the inductive and galvanic data types, respectively, with a model space parameterization that includes induced polarization effects, preventing discrepancies caused by the neglect of capacitive effects.

After assessment of the joint inversion framework through synthetic testing, the methodology is applied to a field study where extensive inductive, galvanic direct current, and IP data have been collected. As expected, the resulting models obtained with independent inversions exhibit differences due to the varying sensitivities of each

method. However, the proposed inversion scheme allows for modelling all datasets with a unique solution that includes induced polarization and fits all data almost equally well than independent inversions.

Furthermore, the comparison between independent and joint results shows a strong enhancement in resolution within the joint model, which identifies electrical anomalies absent in both the galvanic and inductive independent models. These improvements are consistently observed across four different profiles acquired in the same area.

The joint models are validated using EM resistivity borehole measurements and lithological descriptions down to a depth of 208 meters, confirming their ability to resolve resistivity anomalies across all scales — as depicted by the borehole measurements — and outcome unfeasible by independent E&EM methodologies.

Finally, the importance of the inclusion of IP effects in the joint modelling of galvanic and inductive resistivity is assessed, highlighting the importance of IP modelling in EM data even in environmental applications.

We consider the success of joint modelling to stem from the integration of sequential, accurate steps throughout the entire process and we believe it to represent a paradigm shift in high-resolution in E&EM investigations.

Key words: *Joint Inversion, Electrical Properties, Induced Polarization, Electrical Resistivity Tomography (ERT), Electromagnetic Theory*

1.2.1.2 INTRODUCTION

Electrical and Electromagnetic (E&EM) geophysical methods rely on different physical principles, resulting in varying sensitivities when the subsurface electrical properties are investigated. As a result, galvanic and inductive measurements collected on the same point or stretch of land often lead to inversion models that depict electrical anomalies differently. In this work, galvanic measurements refer to DC (direct current) Electrical Resistivity Tomography (ERT) and Induced Polarization (IP), while inductive measurements refer to time-domain electromagnetic techniques with short or zero offset configurations.

Attempts to take advantage of these differing sensitivities have led to the development of E&EM joint inversion methods. Over the years, a broad range of solutions has emerged, with different technical approaches proposed. Since the early stages, efforts to unify these

methods have led to improvements in model resolution (Jupp and Vozoff, 1977), yielding results that could not be achieved with independent approaches (Raiche et al., 1985), mitigating the non-uniqueness issues inherent in E&EM modelling (Albouy et al., 2001), and proving effective also including IP data (Sandberg, 1993).

More recent efforts, particularly with advancements in modern geophysical systems that evolved data acquisition from point-based investigations to 2D and 3D data distributions, have highlighted challenges in reconciling E&EM datasets into a single, well-fitting joint model. It is widely recognized in literature that E&EM measurements are sensitive to different components of subsurface electrical resistivity (Christensen, 2000). Short and zero offset Inductive measurements primarily respond to the horizontal component of resistivity, as eddy currents generated by the decay of the primary magnetic field induce horizontal current flow in the ground. In contrast, galvanic measurements are more sensitive to the geometric mean of both the horizontal and vertical resistivity components. These differences have been identified as a major source of difficulty in performing E&EM joint inversion, as subsurface anisotropy is sensed differently by the two methods. The state-of-the-art suggests that, without the application of specific compensation, data-correction or accepting some degree of approximation, E&EM joint inversion is unfeasible. For example, Meju (2005) introduced a correction for galvanic sounding distortion using inductive measurements before integrating the datasets into a joint inversion, ultimately including the correction coefficient as an inversion parameter. Similarly, Christensen (2000) proposed a coefficient to address the differential effects of subsurface anisotropy on inductive and galvanic data, considering that a necessary condition for the joint inversion. Aside of the specific joint modelling techniques or corrections applied, literature consistently agrees on improvements in resolution achieved when E&EM data are combined. However, a single, validated, standardized and widely recognized joint inversion methodology for the datatypes considered in this study has yet to be established within the geophysical community.

In this work, we propose a joint inversion scheme that integrates E&EM methods within a unique inversion framework, without the need for any data compensation or correction. While acknowledging the points made by previous authors, we consider the discrepancies in resistivity components measured by the two techniques less significant than the accuracy and comprehensiveness required in data acquisition, processing, and modelling.

The proposed joint inversion is characterized by a unified framework where inductive, galvanic, and full-decay galvanic induced polarization data are incorporated within the same inversion kernel. This inversion framework is designed to produce a single model that simultaneously minimizes the misfit across all datasets. The model parameterization features the Maximum Phase Angle reparameterization of the Cole-Cole model, as developed by Fiandaca et al., (2018).

The joint approach starts with the acquisition E&EM data using calibrated systems, with accurately characterized transfer functions, whose incomplete or imprecise inclusion introduces uncertainties already in the independent modelling (e.g., Christiansen et al., 2011), which are further amplified in the joint inversion. The system transfer function is then used to compute the forward responses by defining independent forward meshes for each datatype to optimize the forward response computation. This is achieved by decoupling the forward meshes from the unique model mesh and linking them through interpolation.

Another key aspect in achieving the goal of joint inversion is incorporating the capacitive properties of the ground into the modelling, thereby avoiding an oversimplified representation of reality. For this reason, galvanic full-decay IP data are included in the data space. The polarization properties of the ground are modelled also in the inductive measurements, since their importance is recognized for exploration applications (e.g., Marchant et al., 2014; Kang and Oldenburg, 2016; Viezzoli and Manca, 2020; Viezzoli et al., 2024) and, more recently, also in environmental studies (e.g., Dauti et al., 2022; Fiandaca et al., 2022).

In the following sections, the joint inversion theoretical framework is presented and supported by a synthetic test for assessment in a controlled environment. It is then applied to a field application featured by high-density E&EM data coverage to assess its performance in a real scenario. Here, the independent and joint inversion results are compared and then the joint models are validated using borehole EM resistivity measurements down to a depth of 208 m.

Finally, a sensitivity analysis is conducted to evaluate the significance of including IP effects in the joint modelling of galvanic and inductive resistivity.

1.2.1.3 THEORETICAL FRAMEWORK

MODELLING STRATEGY

Inductive and galvanic geophysical measurements are widely recognized for their differing spatial sensitivities to the components of electrical resistivity, resulting in discrepancies between the independent models obtained from the two methods. The state of the art of E&EM joint inversions highlights the need for introducing correction factors to achieve satisfactory data fitting and resolution improvements, which are deemed necessary to counteract the effects of subsurface anisotropy. This work shifts the focus toward the modelling and, in particular, the inversions are carried out following Fiandaca et al. (2024) with EEMverter, a software specifically designed to jointly model inductive and galvanic data with the inclusion of the IP phenomenon. Regardless of the data type, the inversion employs the first term of the Taylor expansion to linearize the nonlinear relationship between the model parameters and the observed data within an iterative approach. The objective function to be minimized is defined as:

$$Q = \left[\frac{1}{N_d + N_r} \left(\sum_{i=1}^{N_d} \frac{(d_{obs} - d_{forward})^2}{\sigma_{d_i}^2} + \sum_{i,j}^{N_r} \frac{(M_i - M_j)^2}{\sigma_{r_{i,j}}^2} \right) \right]^{\frac{1}{2}} \quad (31)$$

Where N_d is the number of inductive and galvanic observed data points d_{obs} for which the forward computation $d_{forward}$ is performed, N_r represents the number of model roughness constraints between the M parameters values; σ_d and σ_r represent the data and constraint standard deviation, respectively.

Within EEMverter, the forward modelling types incorporates the system transfer function for both inductive and galvanic measurements. Regarding the Time-Domain EM measurements, a 1D forward response is analytically calculated through Eq. (32) which calculates the responses accounting for the receiver's filter characteristics, the transmitter geometry and the current waveform. The forward calculation is performed in the frequency domain (FD) by following the method outlined in Ward and Hohmann (1988), where it is modelled a superimposition of horizontal electric dipoles along the transmitter loop:

$$B_{z,FD}(\sigma, h, \omega, x, y, z) = \oint_{Tx \text{ loop}} dB_{z,FD} \quad (32)$$

where $\sigma = \{\sigma_1, \dots, \sigma_N\}$ and $h = \{h_1, \dots, h_{N-1}\}$ represent the electric conductivity and the layer thicknesses of a N-layered 1D model, ω is the angular frequency x, y, z indicate the position of the receiver and $dB_{z,FD}$ is the contribution of the infinitesimal loop piece of length ds , expressed as:

$$dB_{z,FD}(\sigma, h, \omega, x^*, y^*, z^*) = \frac{I \cdot ds}{4\pi} \cdot \frac{y^*}{\rho^*} \oint_0^\infty (1 + r_{TE}) e^{\mu_0 z^*} \cdot \frac{\lambda^2}{u_0} \cdot J_1(\lambda \cdot \rho^*) \cdot d\lambda \quad (33)$$

where, x^*, y^*, z^* are the receiver coordinates in the reference system that sees the infinitesimal loop piece as oriented in the x direction and centered at its origin, J_1 represents the Bessel function of first order, $\rho^* = (x^{*2} + y^{*2})^{1/2}$ is the distance between the receiver and the segment origin, I is the current in the loop, $u_0 = (\lambda^2 - \omega^2 \mu_0 \epsilon_0)^{1/2}$ and r_{TE} represents the reflection coefficient of the electric field transverse to the z -axis (see, Sullivan et al., 2023).

Regarding the galvanic direct current (DC) and full-decay IP data, the forward response is calculated using a finite-element solution for complex conductivity in the FD (Binley and Kemna, 2005). This response is computed over several decades of frequency and subsequently transformed into the time domain (TD, Johansen and Sørensen, 1979). The forward response assumes a 2D distribution of the complex conductivity and neglects electromagnetic induction. The forward problem for the 2D distribution of complex conductivity $\sigma^*(x, z, \omega)$ at a given frequency ω , with a point source at the origin emitting a (zero-phase) current I , is governed by Poisson's equation, Fourier-transformed in the strike (y) direction (e.g., Weller et al., 1996; Binley and Kemna, 2005):

$$\frac{\partial}{\partial x} \left(\sigma^* \frac{\partial \phi^*}{\partial x} \right) + \frac{\partial}{\partial z} \left(\sigma^* \frac{\partial \phi^*}{\partial z} \right) - \lambda^2 \phi^* \sigma^* = -I \delta(x) \delta(z) \quad (34)$$

Where ϕ^* is the Fourier-transformed complex potential, λ is the Fourier transformation variable associated with the assumed strike (y) direction and δ denotes the Dirac delta function.

The differential equation (Eq. (34)) is solved using the finite element method, applying Neumann and Dirichlet boundary condition. Both the frequency-domain E&EM forward responses are subsequently transformed into the time domain using a fast Hankel transformation (as described in Effersø et al., 1999) for both the forward response and the Jacobian. Specifically, the time-domain Jacobian (J) for the i -th forward mesh is computed as:

$$J_{m_i, TD} = A \cdot T \cdot J_{m_i, FD} \quad (35)$$

Here, the matrix T contains the Hankel coefficients, while the matrix A accounts for the effects of the current waveform, gate integration, and filters. As the data space includes the galvanic full-decay IP signals, is important to underscore that the system transfer function modelling includes the duration of the current pulses. The frequency-domain Jacobian $J_{m_i, FD}$ is computed in 1D using finite differences and in 2D using the adjoint method (as described in Fiandaca et al., 2013) as follows:

$$J_{m_i, FD} = J_{\sigma^*, i} \cdot \frac{\partial \sigma^*}{\partial m_i} \quad (36)$$

Where $J_{\sigma^*, i}$ is the Jacobian of the i -th forward mesh with respect to the complex conductivity σ^* , and $\frac{\partial \sigma^*}{\partial m_i}$ is the partial derivative of the complex conductivity versus the model parameter.

This approach allows for the implementation of any parametrization of the IP phenomenon. In this case, the Maximum Phase Angle (MPA, Fiandaca et al., 2018) reparameterization of the Cole-Cole model (Pelton, 1978) is adopted. This reparameterization of the model space (Eq. (37)) enhances resolution and reduces parameter correlations.

$$m_{MPA \text{ Cole-Cole}} = \{\rho_0, \varphi_{max}, \tau_\varphi, C\} \quad (37)$$

Where ρ_0 is the direct current resistivity, φ_{max} is the maximum phase at the angular frequency $\omega_\varphi = 1/\tau_\varphi$, and τ_φ and C are the relaxation time and the frequency exponent. In the specific case of the field study, presented to validate the joint inversion procedure, the model parameterization also included the system flight height as an inversion parameter for the Airborne EM (AEM) data.

Another important feature of the joint inversion proposed in this work is the definition of multiple forward meshes decoupled from a unique model mesh, which are tailored to optimized the forward responses for the different datatypes (Figure 3). The connection between the model and forward meshes is established by interpolating the model mesh parameters onto the forward mesh discretization, as demonstrated for 1D AEM in Christensen et al., (2017) and for 3D galvanic IP in Madsen et al., (2020). The interpolation of model parameters M , defined at the nodes m_i of the i -th forward mesh is achieved through matrix multiplication. In this process, the matrix F_i holds the interpolation weights, which are determined solely by the distances between the model mesh nodes and the subdivisions of the i -th forward mesh:

$$m_i = f_i(M) = F_i \cdot M \quad (38)$$

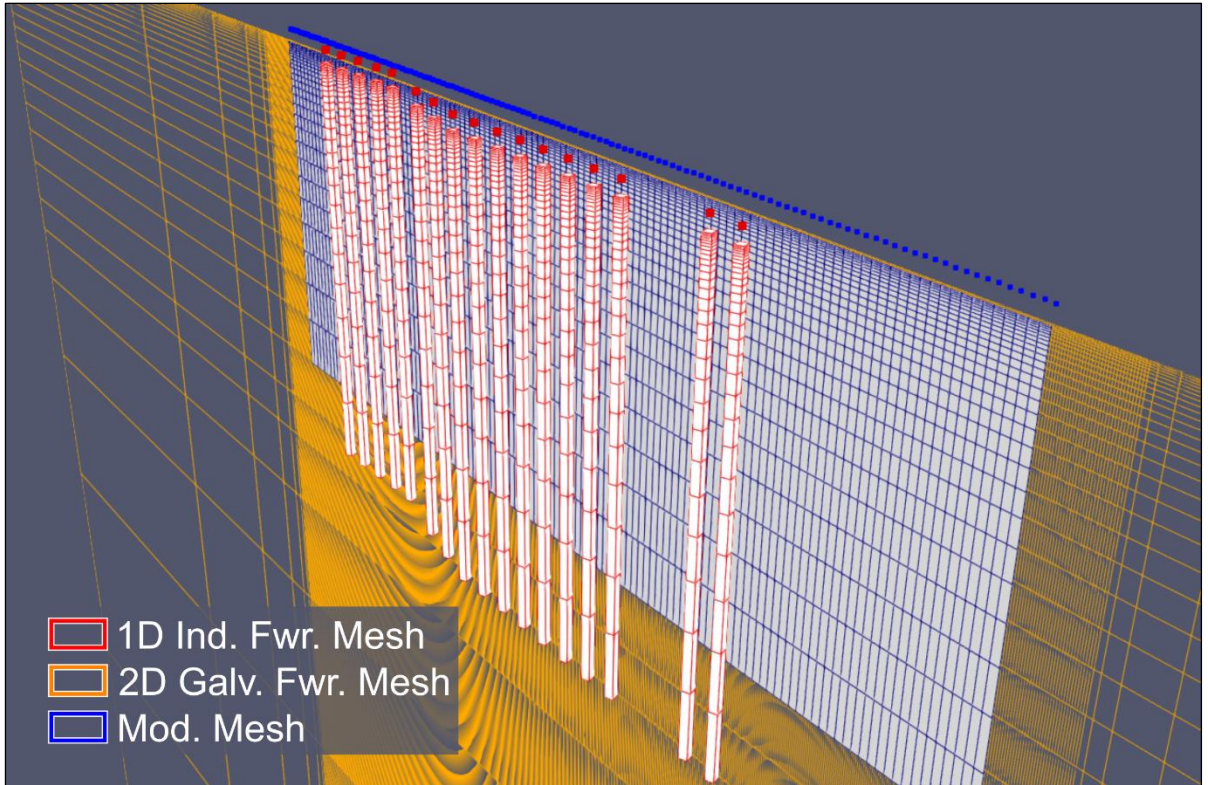


Figure 3: Forward meshes for the 1D inductive (red) and 2D galvanic (orange) computations used in the joint inversion process. The forward responses are calculated on the individual meshes, to be interpolated onto the unified model mesh (blue).

EEMverter also enables the inversion process to be split into multiple cycles, allowing different data groups, inversion settings, and also parameterizations to be sequentially

included, providing an additional means of balancing the joint inversion throughout the iterative process (Eq. (39), where the subscript j indicates the cycle). Figure 4 illustrates this concept, showing the split joint inversion process for the modelling of the real case study. It demonstrates how different data groups are activated across cycles, helping in balancing the data space, particularly when the data distribution is uneven across plane-space and depth. Furthermore, all cycles include data uncertainties, which are incorporated into the model update equation (Eq. (39)) to determine the weight of specific data points through the covariance matrix (C_d), accordingly to their standard deviation.

$$M_{n+1,j} = M_{n,j} + [J_j^T C_d^{-1} J_j + R_j^T C_{R,j}^{-1} R_j + \lambda I]^{-1} \cdot [J_j^T C_d^{-1} (d_j - f_{n,j}) - R_j^T C_{R,j}^{-1} R_j \cdot M_{n,j}] \quad (39)$$

where j represents the inversion cycle index; M is the model vector; J_j is the jacobian for the data used in the j^{th} cycle; R_j and $C_{R,j}$ define the roughness constraints of the j^{th} cycle; d_j and $f_{n,j}$ represent the data and corresponding forward response; λ is the damping and I is the identity matrix.

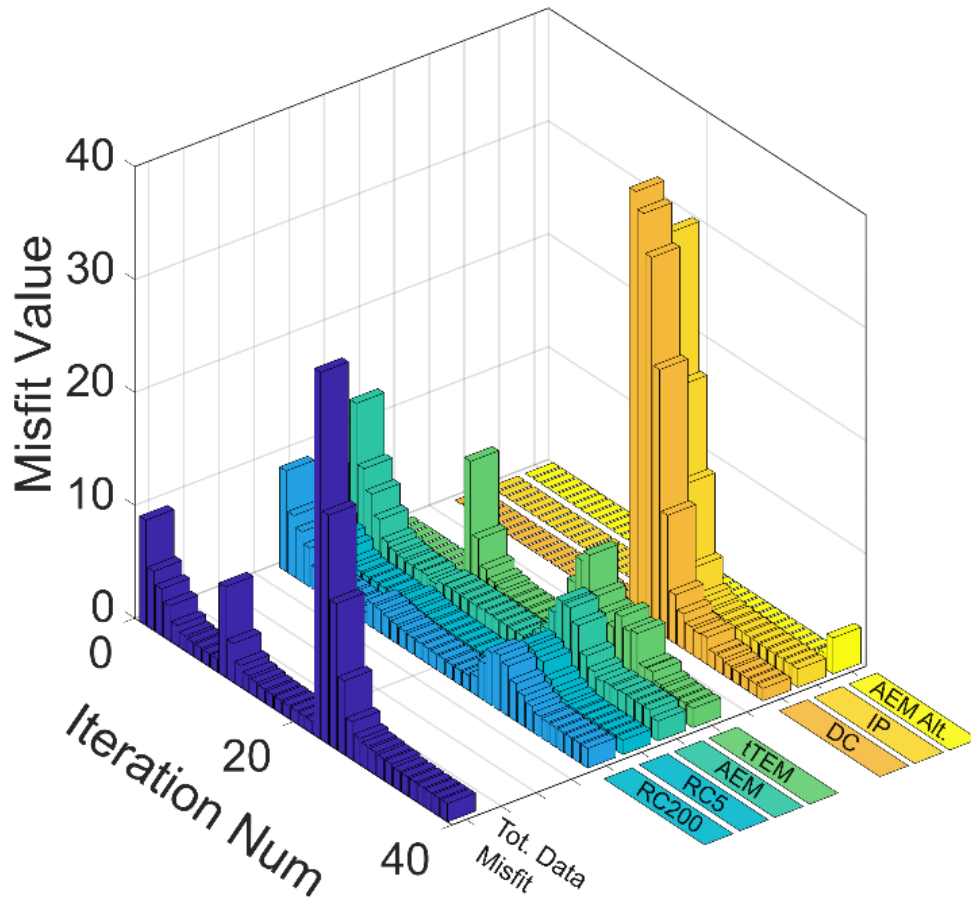


Figure 4: Total and data misfit evolution in a multicycle joint inversion where inductive data are included first and galvanic data later. The highest total misfit occurs when the galvanic datasets are incorporated into the inversion framework (iteration 20).

The modelling also includes the calculation of the Depth of Investigation (DOI) for the models, based on a modification of the method proposed by Vest Christiansen and Auken, (2012) by Fiandaca et al., (2015). This modification involves applying covariance analysis to the inverted model, taking into account the data standard deviations. It enables the estimation of the model reliability and its spatial dependence on the data, their uncertainty and the parameter correlations.

SYNTHETIC TEST

The purpose of the synthetic test is to evaluate the effectiveness of the unified E&EM joint inversion framework in a controlled environment. The primary focus will be on the ability to smoothly integrate inductive and galvanic datasets, featured by differing sensitivities to subsurface features, into a unique model featured by real and complex electrical resistivity parametrization. The IP effects have been modelled considering strength and

spectral content of the polarization typical of environmental applications on unconsolidated formations. In these applications the IP effect is not strong, and it is typically disregarded. However, in this study we want to highlight that, despite IP is difficult to retrieve from inductive-only measurements when weak polarization is present, it still has a significant effect on the data.

The synthetic modelling incorporates four data types, including inductive airborne and ground data, as well as galvanic Direct Current and Induced Polarization (DCIP) data, each accompanied by complete hardware description (e.g. transmitter waveform and receiver filters, see Christiansen et al., 2011). More specifically, the same type of AEM dataset used in the field study (SkyTEM³⁰⁴) is employed, featuring a measuring time window ranging from 1.6E-05 to 3.1E-03 sec. For the ground inductive data, WalkTEM data are included, with a data time range from 1.6E-05 to 1.7E-03 sec. The last type of ground inductive data included is derived from the tTEM system, which features a smaller transmitter area and a data time range between 6.3E-06 and 1.24E-04 sec. For the DCIP measurements, a gradient sequence with electrodes spaced ten meters apart is simulated. All specific details for these different systems can be found in Section 3.1.

For each dataset, a specific forward response is calculated accounting for the different data characteristics and incorporating the system transfer functions. Regarding the data uncertainty, for the inductive data, the uniform relative uncertainty is set at 3%, plus a time-dependent noise decreasing as $t^{-\frac{1}{2}}$ with level equal to $1 \frac{nV}{m^2}$ at 1 ms. For the DC and IP data, a uniform relative uncertainty of 1% and 10% has been assigned, respectively, plus a voltage-dependent noise calculated using a noise voltage threshold of 0.1 mV over an integration time of 0.01 s, following Olsson et al. (2015).

Figure 5 show the results of the synthetic modelling, comparing the performance of the independent inductive inversion (first column) and galvanic inversion (second column) to the joint inversion (third column), which incorporates all the previous data types. The comparison focuses on the ability of each approach to resolve the real and complex conductivity features of a subsurface model described via MPA parametrization.

The subsurface model used for the test is designed to replicate features similar to those described by the borehole presented in Section 3.3, used for the real case study validation. The goal is to assess the performance of the joint inversion relying on a subsurface model representative of real conditions. Thus, the lithological description was first translated

into plausible hydraulic parameters—easier to estimate than MPA values—and subsequently converted into MPA parameters using the petrophysical relationships that link permeability to bulk and imaginary conductivity and to relaxation time (see Römhild et al., 2022, 2024) that holds for unconsolidated and saturated sediment. However, a conglomerate formation has also been modelled, because it is present in the site of the field study. For this reason, the coefficient derived by Weller et al. (2015) for consolidated materials are used in the petrophysical relation between permeability, bulk conductivity and imaginary conductivity in the conglomerate layer. The details of this conversion are presented in Table 1 and

Table 2, which report the subsoil lithologies and depths, along with the assigned hydraulic properties and converted electrical converted properties, respectively.

Table 1: Depths and lithological units of the subsoil model used in the synthetic test.

Depth [m]	Litho	Depth [m]	Litho
0.0	Clay	-79.7	Clay
-2.5	Sand	-93.3	Clay
-5.3	Clay	-108.7	Sand
-8.6	Sand	-126.3	Sand
-12.3	Sand	-146.4	Sand
-16.5	Sand	-169.2	Sand
-21.3	Clay	-195.3	Sand
-26.7	Clay	-224.9	Clay
-33.0	Gravel	-258.7	Clay
-40.0	Gravel	-297.1	Clay
-48.1	Conglomerate	-340.9	Clay
-57.3	Conglomerate	-390.8	Clay
-67.8	Conglomerate	-450.0	Gravel

Table 2: Description of the lithological units used for the synthetic test presented in terms of estimated hydraulic parameters, along with their respective conversion into MPA parameters.

	Clay (C)	Sand (S)	Gravel (G)	Cong. (N)
SigW (mS/m)	3.00E+01	3.00E+01	3.00E+01	3.00E+01
HYC (m/2)	1.00E-08	1.00E-04	1.00E-01	1.00E-06
D+ (m ² /s)	3.80E-12	1.30E-09	1.30E-09	2.00E-10
C (dimless)	5.00E-01	5.00E-01	5.00E-01	5.00E-01
Formation factor (dimless)	5.00E+00	5.00E+00	5.00E+00	3.00E+00
Rho (Ohm.m)	3.52E+01	1.57E+02	1.66E+02	9.74E+02
Phi (mrad)	3.07E+01	2.53E+00	1.29E-01	1.09E+00
Tphi (s)	8.14E-03	2.08E-01	1.00E+02	8.04E-02
C (dimless)	5.00E-01	5.00E-01	5.00E-01	5.00E-01

Figure 5 shows the model derived from the joint inversion (green line in the panels) to outperform the independent models in recovering the true one (black dotted lines) across all parameters. About the independent inversion of the resistivity parameter, the inductive model (blue line) shows higher sensitivity to the low-resistivity zones, whereas the galvanic model (red line) better captures the high-resistivity features. The joint inversion displays improved capability in resolving both low and high resistivity layers, indicating the merging of the different datatype sensitivity, and resolve the shallower conductive layer, which is not imaged by the independent inversions. Regarding the complex conductivity parameters, the improved resolution provided by the joint inversion is confirmed over the independent modelling. In any case, the sensitivity to these parameters primarily originates from the galvanic data, as also indicated by the shallow DOI (red dotted lines in Figure 5 panels) of the inductive models. Nevertheless, the model space exploration enabled by the joint inversion framework aided the recovery of complex conductivity features, further improving upon the independent galvanic models. Furthermore, modelling either the true model or the joint inversion model disregarding IP but keeping the same resistivity structure, generate an inductive forward response with much higher misfit. This demonstrate that even weak polarization, typical

of surveys in environmental applications on unconsolidated formations, has an effect on inductive data.

Accordingly to these results, in the case study presented next, we expect the joint inversion to integrate the different sensitivities of the data types, resulting in subsurface models with higher resolution compared to those obtained from the independent inversions.

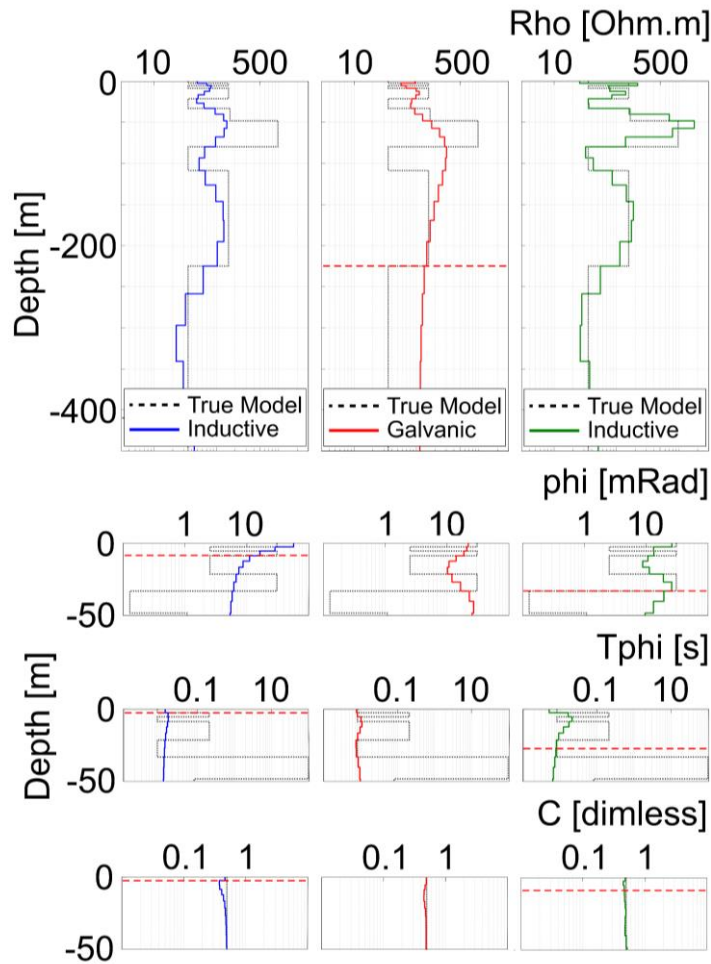


Figure 5: Synthetic comparison of independent and joint inversion performances. In the panels, the black dotted lines represent the true model for the different parameters. The blue lines show the results of the inductive independent inversion, which includes SkyTEM, WalkTEM, and tTEM data types in a unified dataspace. The red lines correspond to the model derived from the independent inversion of galvanic data, while the green lines represent the model obtained from the joint inversion framework.

1.2.1.4 FIELD STUDY AND VALIDATION

The application of the joint inversion approach to a real-field study aims to deeply evaluate the actual performance of the joint procedure, taking now into account all the intrinsic complexities of real data. The focus will be on understanding the challenges involved in performing such a composite study from data acquisition to modelling. The field study was conducted near the southern margin of the Italian Alps, at a site where E&EM measurements were performed to establish a reference site (HydroGeosITe, Signora et al., 2023) for the interpretation of an AEM campaign covering over 20,000-line kilometers. This site was also intended to serve as a calibration reference for future AEM surveys. The geological setting of the area is characterized by complex interdigitations and superimpositions of fluvio-glacial deposits, where diverse geological units exhibit strong spatial heterogeneity, with depositional variations occurring over just a few tens of meters. Consequently, a subsurface resistivity model characterized by high spatial variability and sharp transitions between lithostratigraphic bodies was expected, with resistivity values ranging from a few $\Omega\cdot\text{m}$ in clay-rich deposits to several thousand $\Omega\cdot\text{m}$ in compact stony conglomerates.

GEOPHYSICAL DATA COVERAGE

The success of a joint inversion begins with purposeful planning of the E&EM geophysical measurements. This involves ensuring a balanced spatial distribution of the measurements to achieve a final model with the most uniform data coverage possible, thereby minimizing discrepancies in the joint model that could result from uneven data distribution. The comprehensive E&EM geophysical measurements collected for the site are presented in Figure 6 and detailed in the following subsections.

DCIP survey:

The galvanic DCIP data have been collected using the constant-current ABEM Terrameter LS2 system in a 100% duty cycle energizing scheme (Olsson et al., 2015) with a 4 kHz full-waveform acquisition. The entire raw signal was extracted from the instrument for subsequent gating, harmonic denoising, and drift removal, following Olsson et al., (2016). Approximately 4 km of DCIP data (Figure 6, red-dots lines, for profile lengths refer to Table 4) were measured with 10 m electrode spacing, employing the gradient protocol for

the acquisitions. Each quadrupole acquisition had an on-time duration of 12 seconds with two stacks per measurement and a maximum current setting of 2.5 Amperes (Mean_{QUAD} current: 0.5 Ampere). The number of quadrupoles acquired among the profiles ranges around 2700, depending on the profile length.

AEM survey:

For the AEM data the SkyTEM³⁰⁴ system was employed to survey the site (Figure 6, green dots), representing the electronic and structural evolution of the system as presented by Sorensen and Auken (2004). The SkyTEM³⁰⁴ system features a 342 m² transmitter area, capable of generating up to 3.0E3 and 1.5E5 NIA (product of number of Tx turns, current and area, in Am²) for Low and High Moments, respectively. The dual moment energizing strategy operates with repetition frequencies of 275 Hz (LM) and 25 Hz (HM), providing EM signals over three of time decade, resulting from the LM current shutdown of $\sim 3.3\text{E-}06$ seconds (LM_{OFF_TIME}: 1.018E-03 sec.; HM_{OFF_TIME}: 10E-03 sec., as declared by the manufacturer). The receiver (RX) in SkyTEM³⁰⁴ features an area of 105 m² and is placed in the so called zero-position (Auken et al., 2015), where the Rx_{Z_X} coils geometrically lays in the null-coupled position with the EM primary field components. The effect of current shutdown is limited in the RX by applying HM front gate of 70E-06 sec, which concurs to the filtering characteristics of the receiver together with a low-pass cut-off frequency of 210 kHz. For the SkyTEM³⁰⁴ system the first theoretical measurement is provided at 10.7E-06 seconds (LM), with the latest gate central time at 9.0E-03 seconds (HM). After manual data processing, the actual transients for this site ranged between 15E-06 seconds and 4E-03 seconds, also resulting from the moderate-to-high EM noise at the site.

Ground TEM survey

Several ground transient electromagnetic soundings have been measured with the ABEM WalkTEM2 instrument in central-loop configuration, with the TX-20 transmitter unit featured by a 20 Ampere peak-to-peak maximum current. Thirty 40x40 m² TX-20 EM soundings (Figure 6, blue dots) have been collected performing a dual-moment energization, reaching 10E-03 sec as latest acquisition time. In WalkTEM2 measurements, the fastest TX current shutdown, which determines the timing of the first data point acquisition after the current turn-off, is achieved by selecting the optimal damping resistance for each station. This approach effectively reduces TX ringing effects and

adapts to variations in subsoil resistivity as the measurement location changes. All soundings were measured with two different receivers, RC5 and RC200, with 5 m² and 200 m² effective area, respectively. Each station undergone a staking time of 30 minutes to reduce noise content.

tTEM survey

The tTEM system (Auken et al., 2019) has been employed to acquire more than 55 km of data (Figure 6, yellow dots) through a 3x3 m² transmitter with receiver in offset configuration (-9 meters). The instrument energizes the transmitter in a dual-moment scheme with LM and HM currents of approximately 3 and 30 Amperes, respectively. With a current shutdown time of 4E-06 seconds and a latest time measured of approximately 1E-03 seconds, the tTEM system excels in characterizing the subsurface with high shallow accuracy. It can resolve structures with lateral variations as small as 10 meters and provide reliable models from just a few meters up to approximately 100 meters of depth. Moreover, the system is designed for high productivity, capable of performing continuous EM measurements while being towed by an ATV at a maximum speed of 20 km/h.

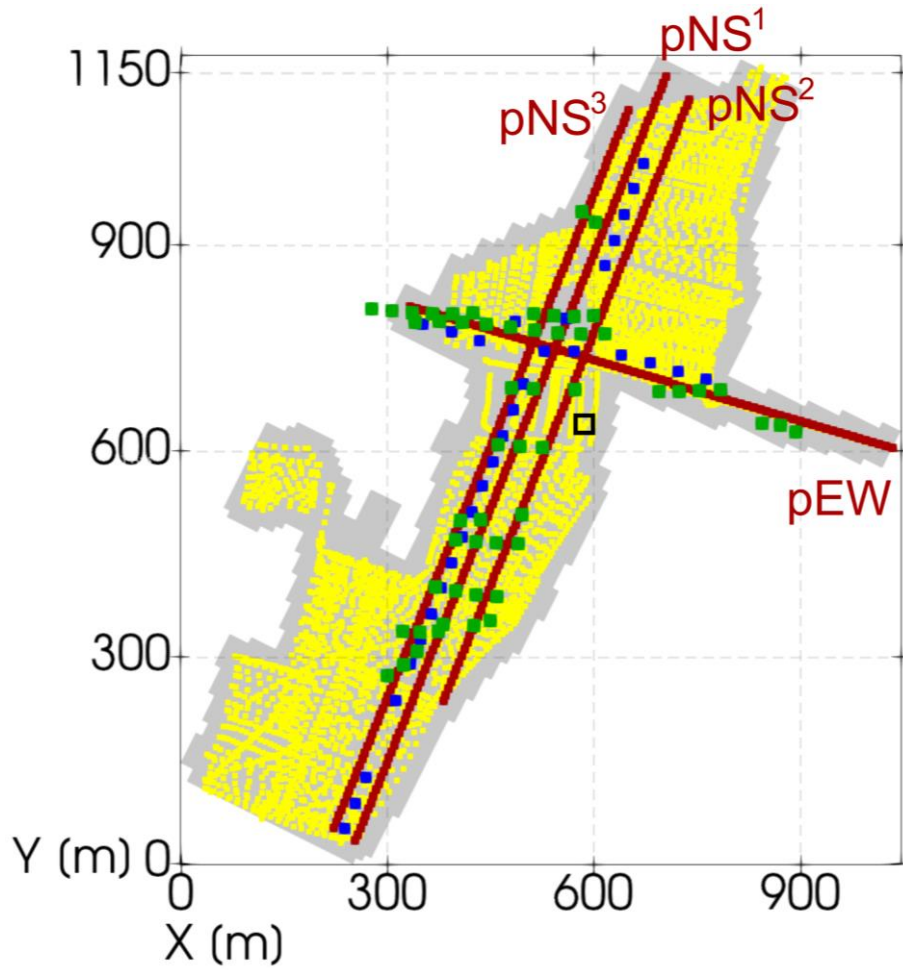


Figure 6: Geophysical data coverage at the HydroGeosITe using both galvanic and inductive methods. Red in-line dots represent the four galvanic DCIP profiles. Green dots indicate the locations of inductive AEM soundings. Blue dots show the ground EM soundings. Yellow dots represent the *t*TEM soundings, which complete the 3D data coverage of the site. The black square reports the borehole location.

DATA MODELLING

The modelling presented in this section aims to extend the synthetic test by applying the joint inversion to real field data and comparing its results with those from independent inversions.

Independent inversion models are presented first, followed by the joint ones, along with descriptions of their respective inversion setups and misfit analyses. For the independent inversions, only the models obtained along the two central DCIP crossing profiles (see Figure 6) are shown for brevity. Conversely, all four models corresponding to the DCIP profiles are presented for the joint inversion to fully evaluate the consistency and

accuracy of the approach. The E&EM joint inversions utilize the same model meshes generated for the galvanic independent modelling. To ensure a comprehensive validation and realistic assessment of the joint inversion's accuracy, no cross-profile constraints are applied between either the crossing or parallel profiles in both the independent and joint inversions.

Before the modelling phase, the inductive, direct current, and induced polarization datasets underwent processing using the EEMstudio software (Sullivan et al., 2024). This free and open-source platform offers advanced tools for processing diverse data types, allowing precision and consistency across all datasets.

Regarding the data uncertainty used in the inversions, a uniform relative uncertainty of 1% and 10% has been assigned to DC and IP data, respectively, plus a voltage-dependent noise (Olsson et al., 2015) as previously presented for the synthetic test. For the inductive data, the uniform relative uncertainty is set at 3% for tTEM and SkyTEM EM datasets, and 5% for WalkTEM dataset, plus the gate-by-gate standard deviation computed through the stacking procedure from each system.

Overall, the mean standard deviation on all datasets is: 1% for DC data; 13% for IP data; 3.2 % for tTEM data; 4.2 % for SkyTEM data (limiting the computations to 200 μ s for LM data and 2 ms for HM data, i.e., times at which the signal is above the noise floor); 8 % for WalkTEM data (always limiting the computations to 200 μ s for LM data and 2 ms for HM data).

INDEPENDENT MODELS

Starting from the EM independent inversion, the soundings to be included along the two main crossing profiles were selected based on a distance criterion (refer to the planar maps of Figure 8a). Specifically, in the WalkTEM, SkyTEM, and tTEM independent inversions, the EM soundings falling within spatial radius of 40, 20, and 5 meters from the profile of interest are respectively included. The EM soundings included in the different profiles are kept consistent for both the independent and joint inversions.

In the misfit calculation, the standard deviation is recalculated accordingly to the data noise content or both the galvanic and inductive datasets (see Section 3.1). An L2 norm is applied to the datasets to favour smoothness within the models, which are discretised with 28 layers that increase logarithmically in thickness from 1.3 to 450 meters in depth.

Figure 7 presents the independent inversions allowing the comparison between the inductive (Figure 7a-c) and galvanic (Figure 7d) independent modelling. The figure highlights the different sensitivities of the two methods in retrieving the high and low resistivity features of the ground. Nevertheless, considering the resolution characteristics of each system, the independent E&EM models appear consistent with each other, depicting coherent resistivity anomalies in the same portions of the models. Specifically, the SkyTEM and WalkTEM models consistently depict a deep low-resistivity feature ($>200\text{m}$), demonstrating limited resolution in the upper parts of sections. However, the WalkTEM model demonstrates higher shallow resolution compared to SkyTEM, likely due to the greater number of aligned soundings and the longer stacking time (~ 30 minutes). The three WalkTEM soundings in the southern portion of the model, shown in Figure 7a, are entirely cropped by the DOI due to their high noise levels. These soundings delineate the southern boundary at the site for large loop EM measurements due to the presence of anthropogenic structures.

The tTEM system provides a more detailed model of the shallow subsurface ($<100\text{ m}$) (Figure 7c), thanks to its smaller transmitter, rapid current turn-off, and the alignment of a large number of soundings along the profile. However, the tTEM model is unable to detect the deep conductor captured by the previous EM models.

The galvanic data produces a model (Figure 7d) with resolution comparable to the tTEM system in the shallow part of the section, though it characterizes the central high-resistivity anomaly differently, assigning to it higher resistivity values. While this model extends to the deeper portions where the SkyTEM and WalkTEM models detect the low-resistivity anomaly, it fails to resolve this feature accurately. This limitation is attributed to several factors among which fewer data points at greater depths, and reduced spatial resolution due to the footprint of the large quadrupole measurements.

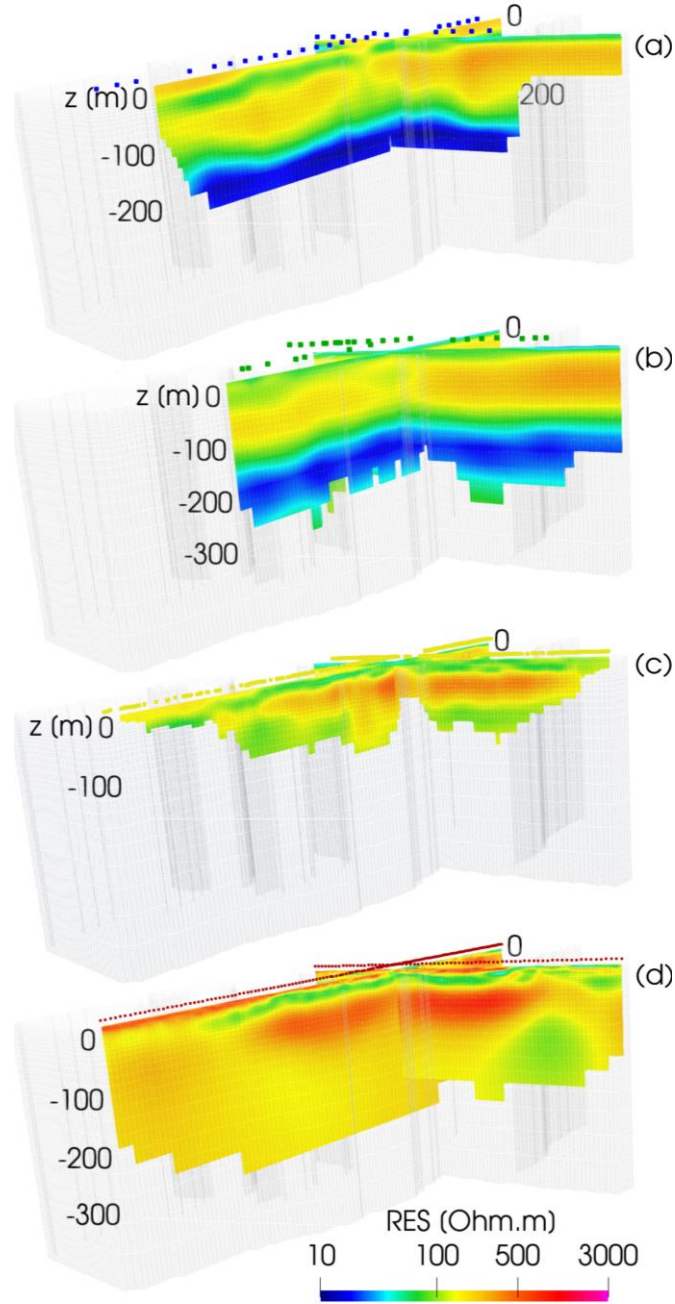


Figure 7: Inversion models from the independent inversions displayed on the same two intersecting sections for each panel. No spatial constraints are enforced between crossing sections. On top of each profile the data position is reported. a) ground TEM independent models. b) AEM independent models. c) tTEM independents models. d) Galvanic independent model. All models are cropped above their DOI. Planar distances can be directly derived from the coordinates on the Z axis.

The misfit analysis of the independent inversion (Table 3) reveals a good fit of the data across all independent inversions, validating the models in terms of statistical reliability. Therefore, it would be difficult to favour one model over another in areas where discrepancies arise. In current practice, when unique interpretations are required, final conclusions are typically drawn from a qualitative integration of the independent models, by selecting one model over the others based on the nature of the target anomalies (e.g., expected resistivity signature and depth), or by incorporating ancillary information for final discrimination.

Table 3: Data misfit for the independent inversions performed along the two intersecting profiles shown in the respective panels of Figure 7. The length and number of data in each profile are reported in Table 4

DATA MISFIT	WalkTEM2 – RC5 / RC200	tTEM	SkyTEM304	Terrameter LS2 – DC / IP
Independent - pNS ¹	0.93 / 0.97	0.72	0.78	1.29 / 1.79
Independent - pEW	1.24 / 0.98	0.68	0.69	1.03 / 1.33

JOINT INVERSION MODELS

With the joint models, the intent is to move beyond the ambiguity of independent inversion results, aiming to produce a unique final model that fits all data simultaneously while integrating the sensitivities of different data types. For the joint results, all models retrieved along the four galvanic lines are presented (Figure 8). The inversions along these profiles are vertically discretised equally for both the model meshes and forward meshes, while variations occur in the x-direction discretization due to differences in profile lengths. The joint framework is designed to be as consistent as possible with the setup used in the previous section for the independent inversions, maintaining equal norms, constraints and the discretization characteristics to ensure unbiased comparison. Figure 8a (pNS¹) presents the joint models along the same two crossing sections previously reported for the independent profiles. In addition, two parallel profiles 50

meters apart in the eastern (pNS², Figure 8b) and western (pNS³, Figure 8c) directions are displayed. All pNS profiles in the panels are crossed by the same pEW profile.

From the initial comparison in Figure 8a (pNS¹-pEW), the joint model reveals a resistivity distribution consistent with the overall anomaly distribution in the independent models. However, the resistivity anomalies are now significantly more defined, with sharper boundaries and, remarkably, revealing new structures absent in the independent models. In addition, the resistivity range is broadened, extending from the minimum values observed in the independent inductive models to the maximum values previously captured only by the galvanic one.

The match between the crossing profiles in Figure 8a (pNS¹ and pEW) shows an almost seamless continuity in the resistivity structures, culminating in a precise match at the crossing point. At this stage, given the significant differences between independent the joint models, it is particularly important to confirm the results consistency in the parallel profiles as well. Figure 8b and 8c display the joint inversion profiles for pNS² and pNS³. Despite the differing lengths of the profiles, the parallel joint inversion models exhibit a resistivity pattern closely matching able with profile pNS¹. They not only depict the main resistivity structures but also reveal lower-order variations likely reflecting spatial heterogeneity.

Table 4 presents the misfit analysis for all the datasets included in the four joint profiles. The misfit increases for almost all datasets compared to the independent procedures (Table 3). However, this increase in value remains within the acceptable range for each dataset, especially considering that nearly all the misfit increase already arises from combining the inductive datasets in a single inversion process, without yet including galvanic data (not shown for brevity).

Table 4: Data misfit values for the joint inversions profiles. The number of data acquired with each system along each profile is indicated in round brackets. For the EM data types, the number of soundings is cumulative of both low and high moments.

DATA MISFIT	WalkTEM2 RC5/RC200	tTEM	SkyTEM ³⁰⁴	Terrameter LS2 DC/IP
Joint - pNS ¹ (1.20 km)	1.13 / 1.98 (38/34 sounds.)	1.14 (341 sounds.)	1.52 (17 sounds.)	1.07 / 1.59 (2773 quads.)

Joint – pEW (0.73 km)	2.21 / 2.65 (20/20 sounds.)	1.33 (343 sounds.)	1.31 (38 sounds.)	2.13 / 1.26 (1180 quads.)
Joint – pNS ² (0.92 km)	1.63 / 2.31 (38/34 sounds.)	1.17 (249 sounds.)	1.14 (24 sounds.)	1.36 / 1.46 (1824 quads.)
Joint – pNS ³ (1.15 km)	1.02/1.86 (28/24 sounds.)	1.21 (268 sounds.)	1.39 (30 sounds.)	1.13 / 1.61 (2332 quads.)

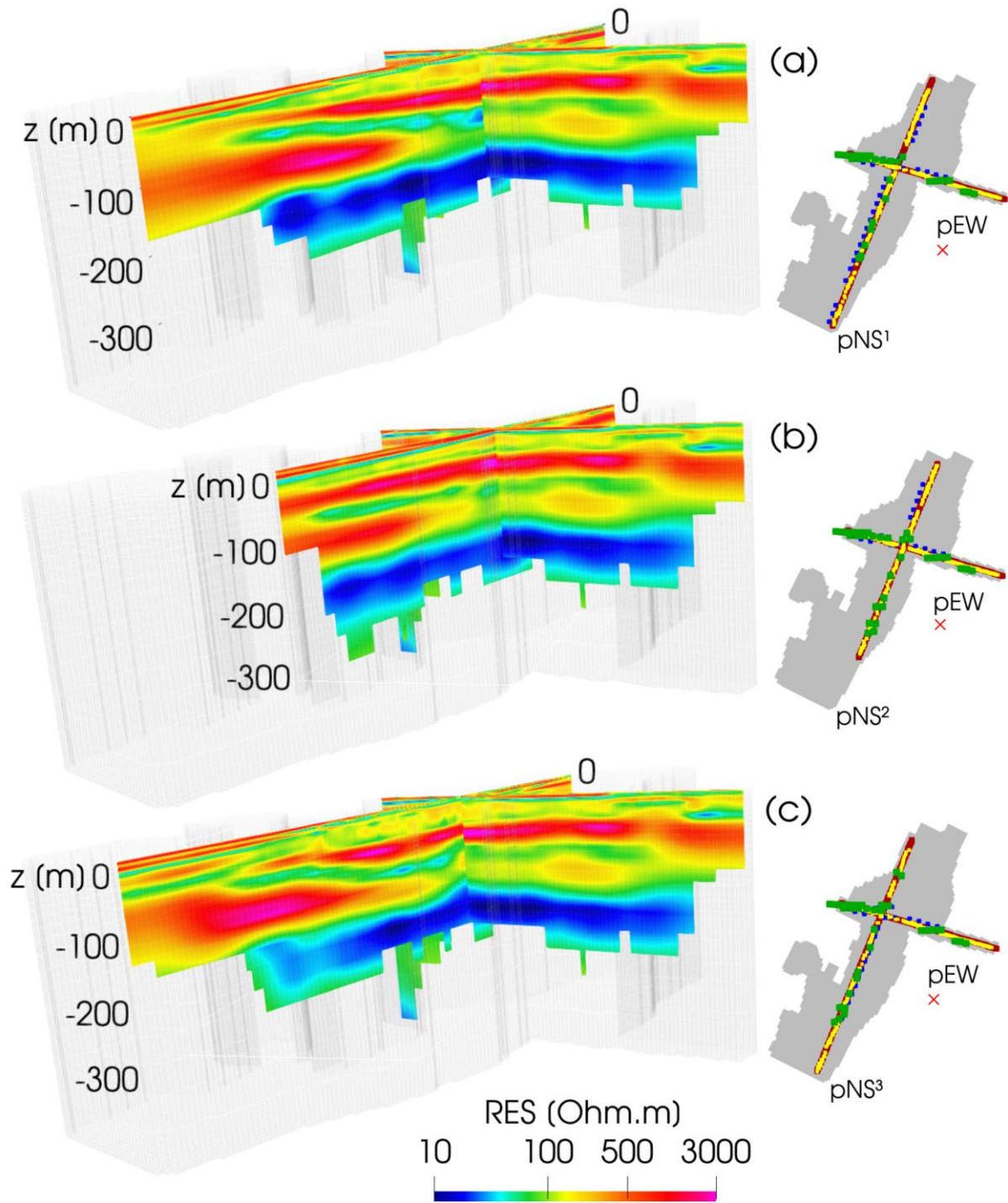


Figure 8: Joint inversion models combining inductive and galvanic data, with positions displayed in the respective planar-view. The pEW profile is retained across all panels for comparisons. a) pNS^1 and pEW joint inversion profiles. b) pNS^2 and pEW joint inversion profiles. c) pNS^3 and pEW joint inversion profiles. No spatial constraints are enforced between crossing profiles. All models are cropped above their DOI. Planar distances can be

directly derived from the coordinates on the Z axis. The red cross in the planar view marks the observation point.

MODEL VALIDATION

The joint models presented in the previous section align with the known geological features of the area, both in terms of morphology and expected absolute resistivity values. In this section the next stage of validation for the E&EM joint models is presented, which more broadly aims to assess the effectiveness of the proposed joint inversion scheme. For this purpose, a borehole 208 meters deep is employed (Figure 6, black square), which intersects the entire fluvio-glacial depositional sequence. EM geophysical logging (logEM) is performed within the borehole along with gamma measurements and lithological description. Additionally, the borehole was drilled using an inverse-push technique, which enabled the continuous collection of drill samples with high representativity and minimal mixing.

The joint procedure validation is carried out through the comparison between the closest joint models (pNS²) and the logEM measurements, as shown in Figure 9, which also includes the comparison with the independent models along the same profile. The logEM measurements and the inversions are completely independent of each other. These comparisons reveal that the joint model better match with the borehole data than the independent inversions, capturing both the main resistivity features and their lower-order variations reflecting subsoil site heterogeneity.

From the logEM and lithological description, starting from the top, after the first ~10 meters of the unsaturated zone, a first-order low-resistivity feature is identified and associated with a clay lithology with a thickness of less than 5 meters and resistivity values ranging between 20-25 $\Omega\cdot\text{m}$. The match between the logEM and the joint model in depicting this geological feature is seamless.

Moving deeper, beyond the first high-resistivity anomaly (~150–170 $\Omega\cdot\text{m}$) observed between -20 and -35 meters, where a gravel aquifer is reported, the logEM detects the strongest high-resistivity feature (~600–700 $\Omega\cdot\text{m}$) at depths ranging from 50 to 100 meters. The joint model retrieves a corresponding feature (>1000 $\Omega\cdot\text{m}$) between -40 and -80 meters, depicting it slightly shallower and more uniform compared to the logEM measurements (see also Figure 10e). The lithological description for this depth interval is

consistent with the resistivity values retrieved, identifying a stony conglomerate with variations in compactness and clay content.

Deeper, the logEM reaches its deepest extent beneath a sequence of heterogeneous sediments where a second aquifer formation is identified at ~ 140 meters ($\sim 150 \Omega \cdot \text{m}$, confirmed by hydraulic testing). At the very bottom, the lowest resistivity anomaly ($\sim 10\text{--}20 \Omega \cdot \text{m}$) is observed in the logEM which appears in the joint model as highly continuous in space and relatively thick (>50 m). Borehole drilling and EM logging terminate at this bottom boundary, which corresponds to a known geological transition in the area, marking the shift from fluvio-glacial deposits ($\sim$ first 200 m) to a marine sequence.

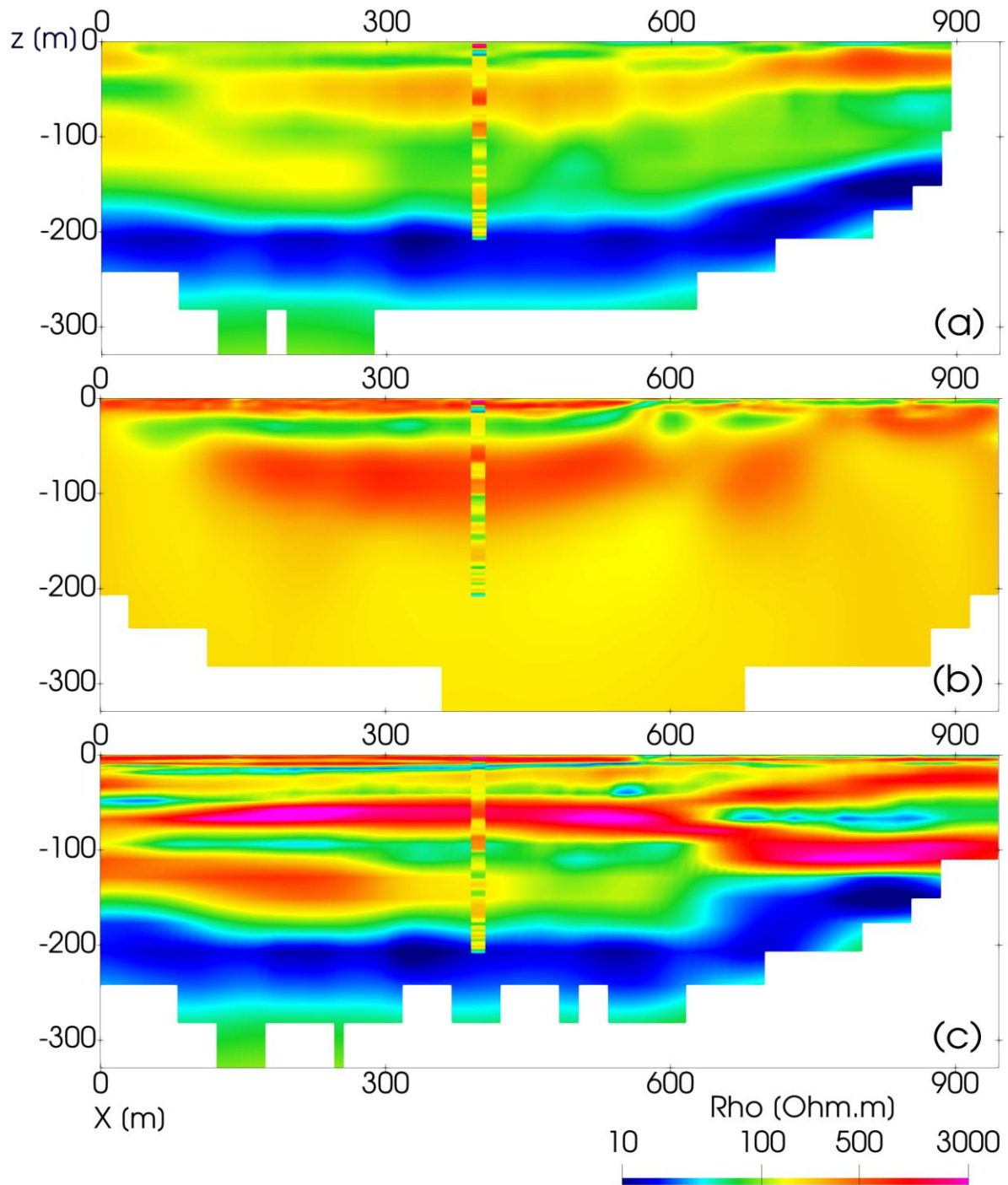


Figure 9: Comparison of the pNS^2 independent and joint models with the results obtained from a log-EM measurements within a borehole drilled 50 meters apart from pNS^2 . a) Inductive model obtained including WalkTEM, SkyTEM and tTEM data. b) Galvanic model. c) Joint model obtained by including all the previous data.

Figure 10e presents the 1D comparison between the five closest joint models, the logEM and logGamma measurements. This overlay confirms the remarkable accuracy of the joint

models in resolving resistivity anomalies across all scales, from the shallow subsurface to the deeper layers. It is worth remembering that the layer thicknesses in the joint inversion model mesh increase logarithmically, whereas the logEM maintains a consistent measurement spacing of one meter throughout the borehole depth.

In the same figure (Figure 10a-d) the comparison is also proposed displaying the 1D models retrieved by the independent inversions. This furthermore highlights how the independent models fail in capturing the complex vertical architecture of the geological layer, despite being able to depict the main subsoil resistivity trends.

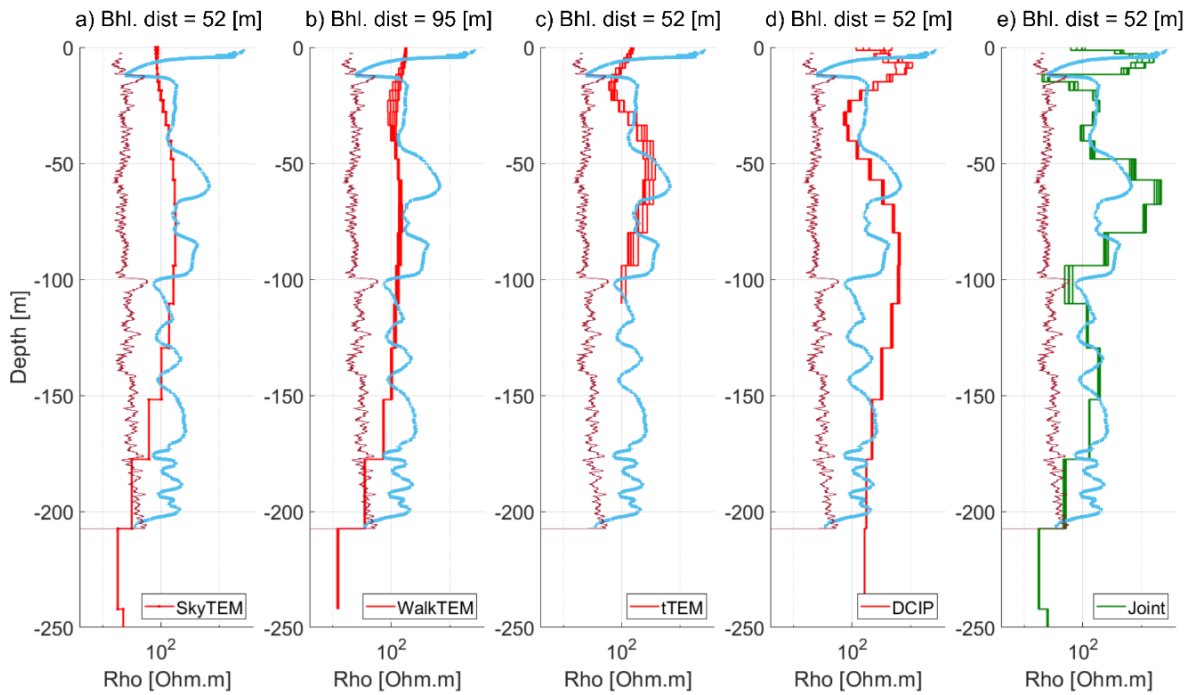


Figure 10: Comparison of independent and joint 1D models extracted from the closest point on pNS^2 to the borehole position. LogEM measurements are shown in light blue and logGamma in red. (a) AEM 1D model; (b) Ground TEM 1D model; (c) tTEM 1D model; (d) Galvanic 1D model; (e) Joint inversion model combining all datasets.

SENSITIVITY ANALYSIS

The E&EM joint inversion approach presented in the previous sections has demonstrated the ability to enhance the model resolution compared to the independent ones, while satisfactorily fitting the data and passing borehole-based validation. These improvements are attributed to the joint framework capability to integrate and balance the different sensitivities of the E&EM datasets.

To verify this claim, a sensitivity analysis is performed to reveal the influence of each data sets on the model parameters. In particular, the sensitivity matrix $G^T C_d^{-1} G$, computed using the Jacobian G of the final iteration of the joint inversion of profile pNS² and the data covariance matrix C_d (Figure 8b), is analysed for the 1D model closest to the borehole location (Figure 11a). Figure 11b presents the sensitivity analysis for each layer of the discretization, highlighting the contributions from inductive (blue line), galvanic (red line), and total sensitivities (black line). The total sensitivity always matches or exceeds the maximum sensitivity of the two individual data types. The inductive contribution is calculated as the sum of all inductive datasets involved in the joint inversion. This analysis reveals which datatype dominates in terms of sensitivity across the different layers, highlighting which dataset primarily drives the model updates (Eq. (39)) during the joint process.

The total sensitivity of the joint inversion aligns, layer by layer, with the highest sensitivity brought alternately by the galvanic and inductive datasets. The EM datasets dominate the sensitivity in low-resistivity layers, while the galvanic dataset enhance the sensitivity in the more resistive sections. Moreover, in some layers, the joint sensitivity exceeds that of the individual datasets.

This confirms that the improved resolution achieved through the E&EM joint inversion stems from the successful integration of different E&EM sensitivities within the unified framework, enabling the joint approach to explore the data space with increased sensitivity across the entire model.

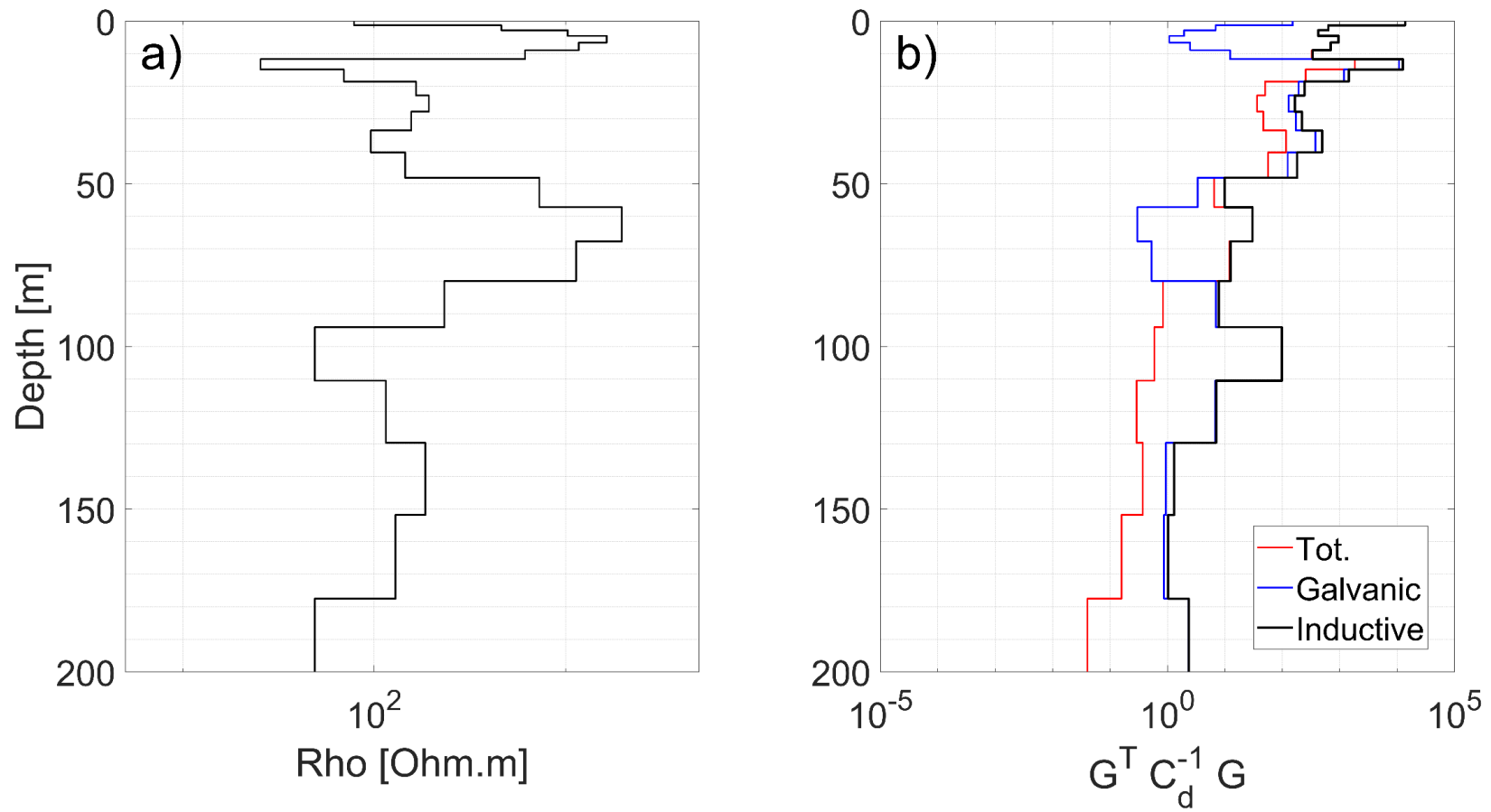


Figure 11: (a) 1D joint inversion model extracted from the point on the pNS^2 profile closest to the borehole. (b) Layer-by-layer sensitivity analysis for the inductive dataset (blue line), galvanic dataset (red line), and the total sensitivity (black line). The inductive contribution is computed as the sum of all inductive datasets included in the joint inversion..

IP MODELLING AND JOINT INVERSION

After validating the joint inversion results and performing the sensitivity analysis, the role of Induced Polarization remains to be addressed. As outlined in Section 1.2.1.3, the joint framework models both the real and complex components of electrical resistivity to fully capture the IP effects, that can influence both galvanic and inductive data.

Figure 12 presents the models obtained from the joint inversion for the complex conductivity MPA parameters along profile pNS². By integrating the information from the subsoil's chargeability models, a new level of interpretative insight into the subsurface is possible. This is further enhanced by combining the information from Figure 12 with and the borehole logEM and corresponding lithological descriptions. First, we can identify the presence of an unsaturated horizon down to 10 meters of depth, characterized by moderate chargeability and lateral heterogeneities. Below this, a highly chargeable horizon is observed between 10 and 15 meters of depth, corresponding to a low-resistivity anomaly in the logEM data and a clay lithology described in the logging report. Beneath, a 20-meter-thick non-chargeable horizon is identified, aligning with a high-resistivity section in the logEM and a lithological description of sandy-gravel, likely representing the first non-chargeable aquifer at the site. Further down, a highly chargeable body extends to the lower boundary of the phi-parameter model, corresponding to a very high-resistivity anomaly in the logEM and to the stony conglomerate interval in the drilling log.

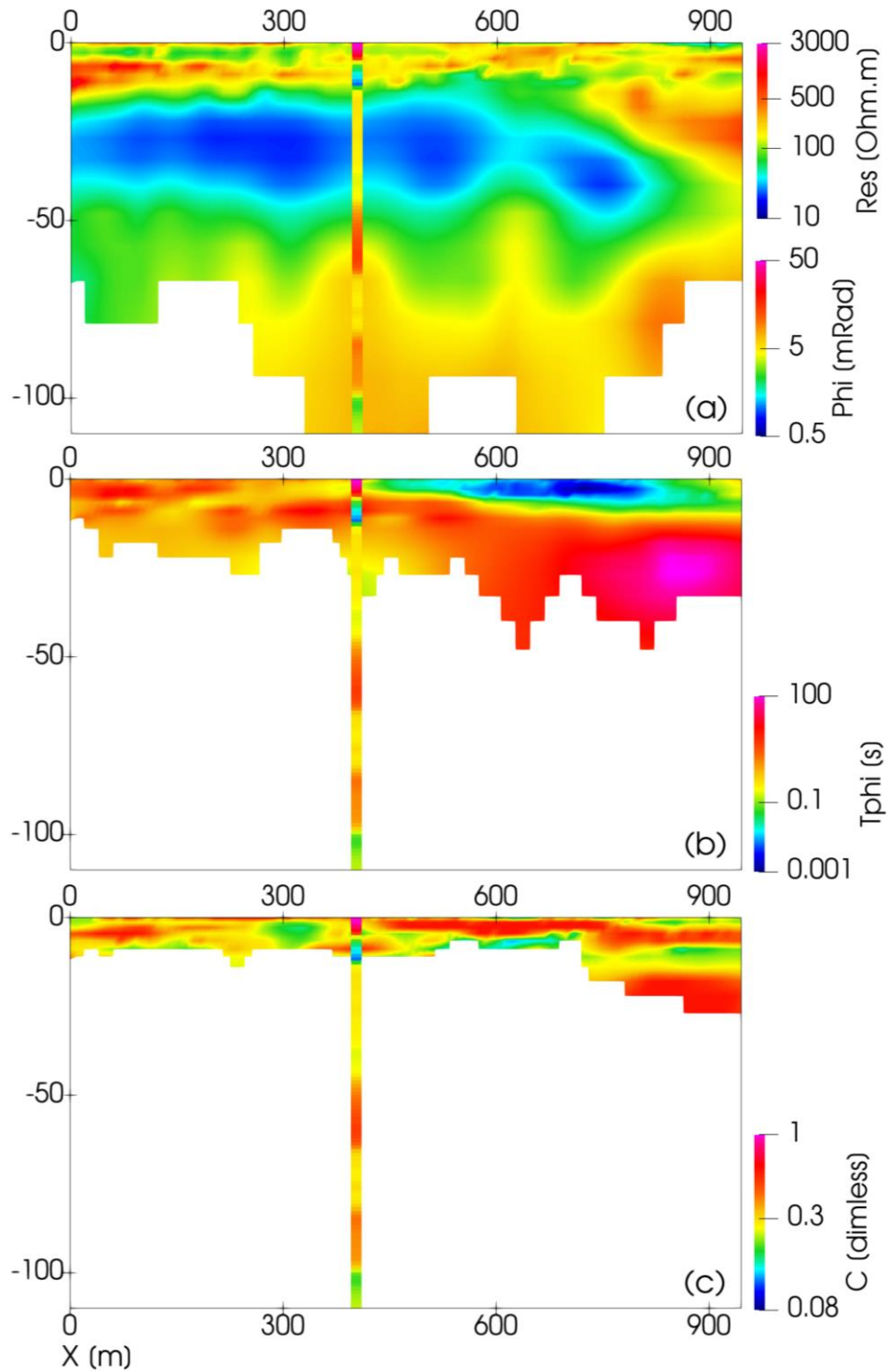


Figure 12: Cole-Cole complex conductivity parameter models derived from the pNS^2 joint inversion. The logEM measurements are overlaid on all panels, with the resistivity legend shown in the upper panel. a) Maximum phase angle joint model. b) Phase relaxation time joint model. c) Broadening parameter C joint model. 5x vertical scale exaggeration compared to previous figures.

To quantitatively evaluate the impact of excluding the IP effect in E&EM joint modelling, Table 5 presents the misfit values for all final joint models carried out with and without IP modelling. This includes both scenarios considering the zero (ρ_0) and infinite (ρ_∞) frequency resistivity values in the RES-only parametrization. The zero-frequency resistivity corresponds to the classic DC resistivity, while the infinite-frequency limit represents the purely-resistivity model that gives the EM response closest to the IP-effected model (Smith and West, 1988). The analysis of Table 5 shows a consistent increase in misfit when IP modelling is not included, in particular for inductive data under the zero-frequency assumption and for galvanic data under the infinite-frequency assumption, accordingly with their respective sensitivity to high and low frequencies. The misfit comparison demonstrates that EM measurements are sensitive to IP effects also in environmental studies, where no strong polarization effects, due for instance to electrode polarization, are present.

For the interpretation of Table 5, it is important to consider that the misfit is weighted by data uncertainty, with EM error bars being larger than those of galvanic DC data (see Section 1.2.1.3). Consequently, with the ρ_0 model, inductive data exhibit a higher percentage difference compared to galvanic data, whereas with the ρ_∞ model, galvanic data show a higher percentage difference.

Table 5: Data misfit of all joint inversions examining the effect of IP modelling on the different E&EM datasets. The scenarios without polarization processes are reported for both the zero-frequency and infinite-frequency electrical resistivity hypothesis.

DATA MISFIT	gTEM - RC5 / RC200)	tTEM	SkyTEM304	TerrameterLS2 – DC / IP
Joint pNS ¹				
MPA	1.13 / 1.98	1.14	1.52	1.07 / 1.59
RES ρ_0	1.26 / 1.87	1.83	1.78	1.71 / -
RES ρ_∞	1.21 / 1.98	1.40	1.62	2.91 / -
Joint pEW				
MPA	2.21 / 2.65	1.33	1.31	2.13 / 1.26
RES ρ_0	2.84 / 3.26	2.30	2.49	2.58 / -
RES ρ_∞	3.08 / 3.00	2.78	1.94	4.06 / -
Joint pNS ²				
MPA	1.69 / 2.31	1.17	1.14	1.36 / 1.46
RES ρ_0	1.80 / 2.31	1.71	1.70	1.74 / -
RES ρ_∞	1.64 / 2.25	1.27	1.25	2.76 / -
Joint pNS ³				
MPA	1.02 / 1.86	1.21	1.39	1.13 / 1.61
RES ρ_0	1.15 / 1.99	1.63	1.98	1.48 / -
RES ρ_∞	1.21 / 1.81	1.44	1.47	2.64 / -

1.2.1.5 CONCLUSIONS

In this work, we presented an inversion scheme for the joint inversion of electrical and electromagnetic (E&EM) datasets that does not require any data compensation prior to the modelling. The approach integrates the system transfer function within a unified data space and introduces key features for balancing the joint inversion, including the disentanglement of model and forward meshes and multiple inversion cycles to progressively incorporate datasets. Additionally, the model space parameterization

accounts for induced polarization (IP), preventing any possible discrepancies from the neglect of capacitive effects.

We applied this joint inversion scheme to a field site densely characterized by both galvanic and inductive measurements. The comparison with independent modelling results revealed higher resolution of the joint models, featuring sharper anomalies over a wider resistivity range and defining entirely new structures that remained undetected in the independent E&EM models.

These results were confirmed across four different profiles at the site and validated using logEM resistivity measurements from a 208 meters deep borehole. The comparison with the borehole measurements revealed the superior ability of the joint modelling in resolving the resistivity anomalies across all scales and throughout the entire investigated depth. In contrast, the smoothed resistivity distribution in the independent models failed to capture the complex details of the site geological architecture.

The sensitivity analysis conducted on the joint model employed for the validation revealed that the increased resolution stems from the enhancement of total sensitivity in the joint inversion, which, layer by layer, aligns with the highest sensitivity contributed alternately by the galvanic and inductive datasets.

Finally, the impact of including the IP effect in the model parameterization was assessed, demonstrating the importance of accounting for capacitive effects in E&EM modelling also for inductive data, even in this environmental application with low-chargeability geological deposits.

We believe that the E&EM joint inversion developed and applied in this study represents a significant step forward in galvanic and inductive high resolution studies.

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REFERENCES

Albouy, Y., Andrieux, P., Rakotondraso, G., Ritz, M., Descloitres, M., Join, J.-L., Rasolomanana, E., 2001. Mapping Coastal Aquifers by Joint Inversion of DC and TEM Soundings-Three Case Histories. *Groundwater* 39, 87–97.
<https://doi.org/10.1111/j.1745-6584.2001.tb00354.x>

- Auken, E., Christiansen, A.V., 2004. Layered and laterally constrained 2D inversion of resistivity data. *GEOPHYSICS* 69, 752–761. <https://doi.org/10.1190/1.1759461>
- Auken, E., Christiansen, A.V., Jacobsen, L.H., Sørensen, K.I., 2008. A resolution study of buried valleys using laterally constrained inversion of TEM data. *Journal of Applied Geophysics* 65, 10–20. <https://doi.org/10.1016/j.jappgeo.2008.03.003>
- Auken, E., Christiansen, A.V., Kirkegaard, C., Andersen, K., Finadaca, G., Sørensen, K., Nyboe, N., 2015. An overview of the newest SkyTEM and inversion technologies with focus on resolution of shallow geological layers. Presented at the EAGE/DGG Workshop on Airborne Geophysics 2015, Hannover, Germany. <https://doi.org/10.3997/2214-4609.201411989>
- Auken, E., Foged, N., Larsen, J.J., Lassen, K.V.T., Maurya, P.K., Dath, S.M., Eiskjær, T.T., 2019. tTEM — A towed transient electromagnetic system for detailed 3D imaging of the top 70 m of the subsurface. *GEOPHYSICS* 84, E13–E22. <https://doi.org/10.1190/geo2018-0355.1>
- Binley, A., Kemna, A., 2005. DC Resistivity and Induced Polarization Methods, in: Rubin, Y., Hubbard, S.S. (Eds.), *Hydrogeophysics*, Water Science and Technology Library. Springer Netherlands, Dordrecht, pp. 129–156. https://doi.org/10.1007/1-4020-3102-5_5
- Christensen, N.B., 2022. Joint inversion of airborne TEM data and surface geoelectrical data. The Egebjerg case. *Journal of Applied Geophysics* 196, 104511. <https://doi.org/10.1016/j.jappgeo.2021.104511>
- Christensen, N.B., 2000. Difficulties in determining electrical anisotropy in subsurface investigations. *Geophysical Prospecting*.
- Christensen, N.K., Ferre, T.P.A., Fiandaca, G., Christensen, S., 2017. Voxel inversion of airborne electromagnetic data for improved groundwater model construction and prediction accuracy. *Hydrol. Earth Syst. Sci.* 21, 1321–1337. <https://doi.org/10.5194/hess-21-1321-2017>
- Christiansen, A.V., Auken, E., Foged, N., Sørensen, K.I., 2007. Mutually and laterally constrained inversion of CVES and TEM data: a case study. *Near Surface Geophysics* 5, 115–123. <https://doi.org/10.3997/1873-0604.2006023>

- Christiansen, A.V., Auken, E., Viezzoli, A., 2011. Quantification of modeling errors in airborne TEM caused by inaccurate system description. *GEOPHYSICS* 76, F43–F52. <https://doi.org/10.1190/1.3511354>
- Dauti, F., Viezzoli, A., Fiandaca, G., 2022. Induced Polarization Effects in Loupe Electromagnetic System 2022, 1–5. <https://doi.org/10.3997/2214-4609.202220185>
- De Stefano, M., Golfré Andreasi, F., Re, S., Virgilio, M., Snyder, F.F., 2011. Multiple-domain, simultaneous joint inversion of geophysical data with application to subsalt imaging. *GEOPHYSICS* 76, R69–R80. <https://doi.org/10.1190/1.3554652>
- Effersø, F., Auken, E., Ingvar Sørensen, K., 1999. Inversion of band-limited TEM responses. *Geophysical Prospecting* 47, 551–564. <https://doi.org/10.1046/j.1365-2478.1999.00135.x>
- Fiandaca, G., Chen, J., Zhang, B., 2024. EEMverter, a New Modelling Tool for Electric and Electromagnetic Data with Focus on Induced Polarization, in: NSG 2024 30th European Meeting of Environmental and Engineering Geophysics. Presented at the NSG 2024 30th European Meeting of Environmental and Engineering Geophysics, European Association of Geoscientists & Engineers, Helsinki, Finland, pp. 1–5. <https://doi.org/10.3997/2214-4609.202420166>
- Fiandaca, G., Christiansen, A.V., Auken, E., 2015. Depth of Investigation for Multi-parameters Inversions 2015, 1–5. <https://doi.org/10.3997/2214-4609.201413797>
- Fiandaca, G., Dauti, F., Signora, A., 2022. Effect of Induced Polarization on Galvanic and Inductive Data: Where is it Stronger? 2022, 1–5. <https://doi.org/10.3997/2214-4609.202220193>
- Fiandaca, G., Madsen, L.M., Maurya, P.K., 2018. Re-parameterisations of the Cole–Cole model for improved spectral inversion of induced polarization data. *Near Surface Geophysics* 16, 385–399. <https://doi.org/10.3997/1873-0604.2017065>
- Fiandaca, G., Ramm, J., Binley, A., Gazoty, A., Christiansen, A.V., Auken, E., 2013. Resolving spectral information from time domain induced polarization data through 2-D inversion. *Geophysical Journal International* 192, 631–646. <https://doi.org/10.1093/gji/ggs060>

- Gallardo, L.A., Meju, M.A., 2011. Structure-coupled multiphysics imaging in geophysical sciences. *Reviews of Geophysics* 49, 2010RG000330. <https://doi.org/10.1029/2010RG000330>
- Gunther, T., Rucker, C., n.d. A New Joint Inversion Approach Applied to the Combined Tomography of DC Resistivity and Seismic Refraction Data.
- Johansen, H.K., Sørensen, K., 1979. FAST HANKEL TRANSFORMS*. *Geophysical Prospecting* 27, 876–901. <https://doi.org/10.1111/j.1365-2478.1979.tb01005.x>
- Kang, S., Oldenburg, D.W., 2016. On recovering distributed IP information from inductive source time domain electromagnetic data. *Geophys. J. Int.* 207, 174–196. <https://doi.org/10.1093/gji/ggw256>
- Lochbühler, T., Doetsch, J., Brauchler, R., Linde, N., 2013. Structure-coupled joint inversion of geophysical and hydrological data. *GEOPHYSICS* 78, ID1–ID14. <https://doi.org/10.1190/geo2012-0460.1>
- Madsen, L.M., Fiandaca, G., Auken, E., 2020. 3-D time-domain spectral inversion of resistivity and full-decay induced polarization data—full solution of Poisson’s equation and modelling of the current waveform. *Geophysical Journal International* 223, 2101–2116. <https://doi.org/10.1093/gji/ggaa443>
- Marchant, D., Haber, E., Oldenburg, D.W., 2014. Three-dimensional modeling of IP effects in time-domain electromagnetic data. *GEOPHYSICS* 79, E303–E314. <https://doi.org/10.1190/geo2014-0060.1>
- Meju, M.A., 2005. Simple relative space–time scaling of electrical and electromagnetic depth sounding arrays: implications for electrical static shift removal and joint DC-TEM data inversion with the most-squares criterion. *Geophysical Prospecting* 53, 463–479. <https://doi.org/10.1111/j.1365-2478.2005.00483.x>
- Olsson, P.-I., Dahlin, T., Fiandaca, G., Auken, E., 2015. Measuring time-domain spectral induced polarization in the on-time: decreasing acquisition time and increasing signal-to-noise ratio. *Journal of Applied Geophysics* 123, 316–321. <https://doi.org/10.1016/j.jappgeo.2015.08.009>

- Olsson, P.-I., Fiandaca, G., Larsen, J.J., Dahlin, T., Auken, E., 2016. Doubling the spectrum of time-domain induced polarization by harmonic de-noising, drift correction, spike removal, tapered gating and data uncertainty estimation. *Geophys. J. Int.* 207, 774–784. <https://doi.org/10.1093/gji/ggw260>
- Pelton, W.H., Rijo, L., Swift, C.M., 1978. INVERSION OF TWO-DIMENSIONAL RESISTIVITY AND INDUCED-POLARIZATION DATA. *GEOPHYSICS* 43, 788–803. <https://doi.org/10.1190/1.1440854>
- Raiche, A.P., Jupp, D.L.B., Rutter, H., Vozoff, K., 1985. The joint use of coincident loop transient electromagnetic and Schlumberger sounding to resolve layered structures. *GEOPHYSICS* 50, 1618–1627. <https://doi.org/10.1190/1.1441851>
- Römhild, L., Fiandaca, G., Bayer, P., 2024. Joint inversion of induced polarization and hydraulic tomography data for hydraulic conductivity imaging. *Geophysical Journal International* 238, 960–973. <https://doi.org/10.1093/gji/ggae197>
- Römhild, L., Fiandaca, G., Hu, L., Meyer, L., Bayer, P., 2022. Imaging hydraulic conductivity in near-surface aquifers by complementing cross-borehole induced polarization with hydraulic experiments. *Advances in Water Resources* 170, 104322. <https://doi.org/10.1016/j.advwatres.2022.104322>
- Sandberg, S.K., 1993. EXAMPLES OF RESOLUTION IMPROVEMENT IN GEOELECTRICAL SOUNDINGS APPLIED TO GROUNDWATER INVESTIGATIONS¹. *Geophysical Prospecting* 41, 207–227. <https://doi.org/10.1111/j.1365-2478.1993.tb00866.x>
- Signora, A., Galli, S., Gisolo, M., Fiandaca, G., 2023. The HydroGeosITe for AEM mapping: characterization through joint inversion of AEM, ground EM and DCIP data. Presented at the 8th International Airborne Electromagnetics Workshop, Zenodo, Fitzroy Island, Queensland, Australia. <https://doi.org/10.5281/zenodo.10067884>
- Smith, R.S., West, G.F., 1988. Inductive interaction between polarizable conductors: An explanation of a negative coincident-loop transient electromagnetic response. *GEOPHYSICS* 53, 677–690. <https://doi.org/10.1190/1.1442502>

- Sorensen, K.I., Auken, E., 2004. SkyTEM—a New High-resolution Helicopter Transient Electromagnetic System. *Exploration Geophysics* 35, 194–202. <https://doi.org/10.1071/EG04194>
- Sullivan, N.A.L., Gisolo, M., Spagnoli, L., Rapiti, A., Dauti, F., Menghini, A., Viezzoli, A., Fiandaca, G., 2023. Airborne EM in northern Italy for sustainable and resilient management of groundwater resources. *Il Nuovo Cimento C* 46, 1–11. <https://doi.org/10.1393/ncc/i2023-23068-y>
- Sullivan, N.A.L., Viezzoli, A., Fiandaca, G., 2024. EEMstudio: Process and Model Electric and Electromagnetic Data with a QGIS Plugin 2024, 1–5. <https://doi.org/10.3997/2214-4609.202420154>
- Vest Christiansen, A., Auken, E., 2012. A global measure for depth of investigation. *GEOPHYSICS* 77, WB171–WB177. <https://doi.org/10.1190/geo2011-0393.1>
- Viezzoli, A., Christiansen, A.V., Auken, E., Sørensen, K., 2008. Quasi-3D modeling of airborne TEM data by spatially constrained inversion. *GEOPHYSICS* 73, F105–F113. <https://doi.org/10.1190/1.2895521>
- Viezzoli, A., Dauti, F., Mule, S., Munday, T., Brodie, R., Fiandaca, G., Farinelli, S., 2024. Modelling IP in Tempest data: the first preliminary steps and insights. Presented at the ASEG DISCOVER Symposium (ASEG), Zenodo, Hobart, Australia. <https://doi.org/10.5281/zenodo.13918379>
- Viezzoli, A., Manca, G., 2020. On airborne IP effects in standard AEM systems: tightening model space with data space. *Exploration Geophysics* 51, 155–169. <https://doi.org/10.1080/08123985.2019.1681895>
- Vozoff, K., Jupp, D.L.B., 2007. Joint Inversion of Geophysical Data. *Geophysical Journal of the Royal Astronomical Society* 42, 977–991. <https://doi.org/10.1111/j.1365-246X.1975.tb06462.x>
- Ward, S.H., Hohmann, G.W., 1988. *Electromagnetic Methods in Applied Geophysics: Volume 1, Theory*. Society of Exploration Geophysicists. <https://doi.org/10.1190/1.9781560802631>

Weller, A., Seichter, M., Kampke, A., 1996. Induced-polarization modelling using complex electrical conductivities. *Geophysical Journal International* 127, 387–398.
<https://doi.org/10.1111/j.1365-246X.1996.tb04728.x>

Weller, A., Slater, L., Binley, A., Nordsiek, S., Xu, S., 2015. Permeability prediction based on induced polarization: Insights from measurements on sandstone and unconsolidated samples spanning a wide permeability range. *GEOPHYSICS* 80, D161–D173.
<https://doi.org/10.1190/geo2014-0368.1>

1.3 CALIBRATION ADVANCEMENTS FOR EM SYSTEMS

In the previous sections (Sections 1.1.1.3 and 1.1.2.2), we presented the state of the art in the calibration of E&EM systems. Now, with a specific focus on inductive systems, we introduce a novel approach to their field calibration, aiming to elevate this process to the highest standard therefore ensuring consistent, compatible, and reliable results when conducting measurements with different instruments.

One of the first crucial factors in EM system calibration is the accuracy and precision through which the test line is characterized. It is essential that the calibration stretch is resolved better, or at least to the same degree, than the system being calibrated. This ensures that the reference model, used to compute the reference response, exceeds the resolution capability of the under-calibration system. Otherwise, ambiguities may arise, leading to uncertainty about which signal should be used to calibrate the other. For this purpose, we intend to employ the joint inversion presented in Section 1.2.1 to provide the model through which calibration will be conducted. The reason for using a joint model to derive the calibration models is that it is considered to provide the most representative and comprehensive description of the subsoil electrical properties, surpassing the insights offered by individual E&EM systems alone (see Section 1.2.1.4). This enhanced description arises from the broader joint data space used to characterize the calibration stretch (Figure 13). This expanded data space allows in fact for the incorporation of the different sensitivities of E&EM data and, by employing a multi-system approach, enables subsoil characterization across a wider range of measurement frequencies. As instance of this, Figure 13 presents all measurements collected at the field site described in Section 1.2.1.4 for performing the joint inversion. Figure 13a shows the various EM transients collected with different EM systems, including two larger transmitter systems with areas of 100x100 and 200x200 meters. Figure 13b displays all transients after normalization by their respective transmitter areas, revealing their compatibility. Meanwhile, Figure 13c, d, and e show the high-density galvanic data collected along the same stretch, subsequently integrated into the joint framework.

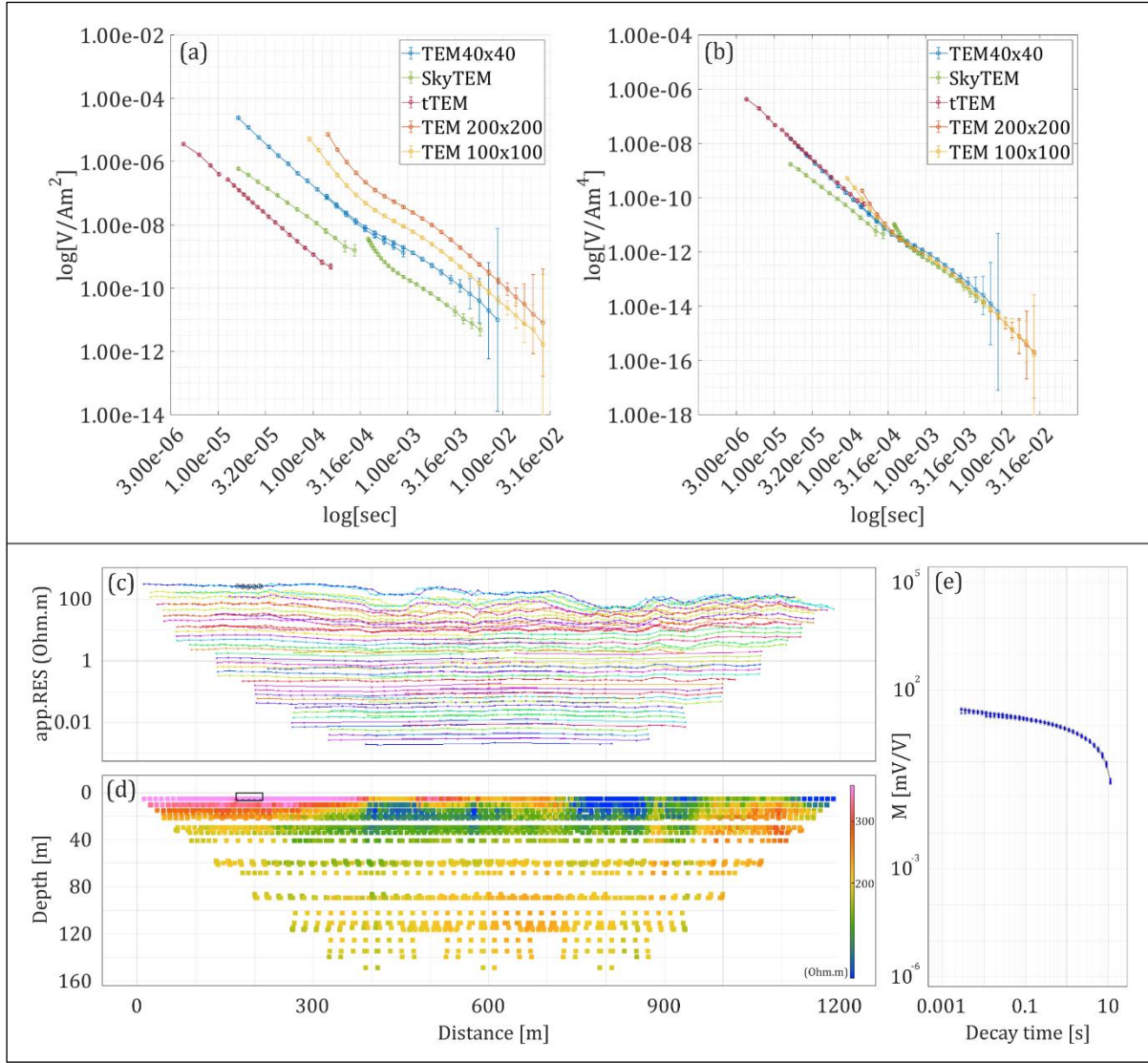


Figure 13: Inductive and galvanic data acquired to perform a joint inversion analysis a) Inductive data collected from the different EM systems. b) Same inductive data but normalized by the transmitter area. c, d) Apparent resistivity sections from galvanic measurements. Upper panel: colours indicate different pseudo depths; lower panel: colours represent apparent resistivity from quadrupole measurements. e) IP decays for the quadrupole measurements marked in panel (c) and (d) by the black rectangle.

As stated, the calibration advancements proposed next are intended to take advantage of the more comprehensive and higher-resolution subsoil model provided by the joint inversion. Nevertheless, this new calibration approach aims to go beyond just employing the joint model to establish the reference model; it also involves a broader evaluation of the site and the varying environmental conditions under which the calibration is performed.

1.3.1 THE JOINT E&EM INVERSION AS CALIBRATION PROCEDURE

By characterizing the calibration stretch with a high-resolution model obtained through the joint approach—combining inductive and galvanic measurements—future calibration efforts will likely benefit, especially as calibration systems continue to improve in resolution. More generally, having a higher-resolution model is always advantageous for instrument calibration. If joint inversion achieves this without increasing the misfit of the model used for calibration, it becomes an obvious choice.

In this context, Figure 14 presents an exercise based on modelling results derived from the real-field central profile shown in Figure 10.

In this exercise, three possible calibration forward signals were generated from the models obtained by i) including only ground TEM data with 40x40 m loop size and the available AEM data for the site (Figure 14a), ii) adding tTEM data with a small loop size to improve resolution in the shallow part (Figure 14b), and iii) incorporating the galvanic DCIP dataset for full joint modelling. From the first to the third case, the model resolution increases significantly.

Figure 14d and Figure 14e present the forward responses, in this case computed for a SkyTEM system, alongside data measured on the site (black line). Detailed description of the SkyTEM AEM system can be found in Section 1.2.1.4.

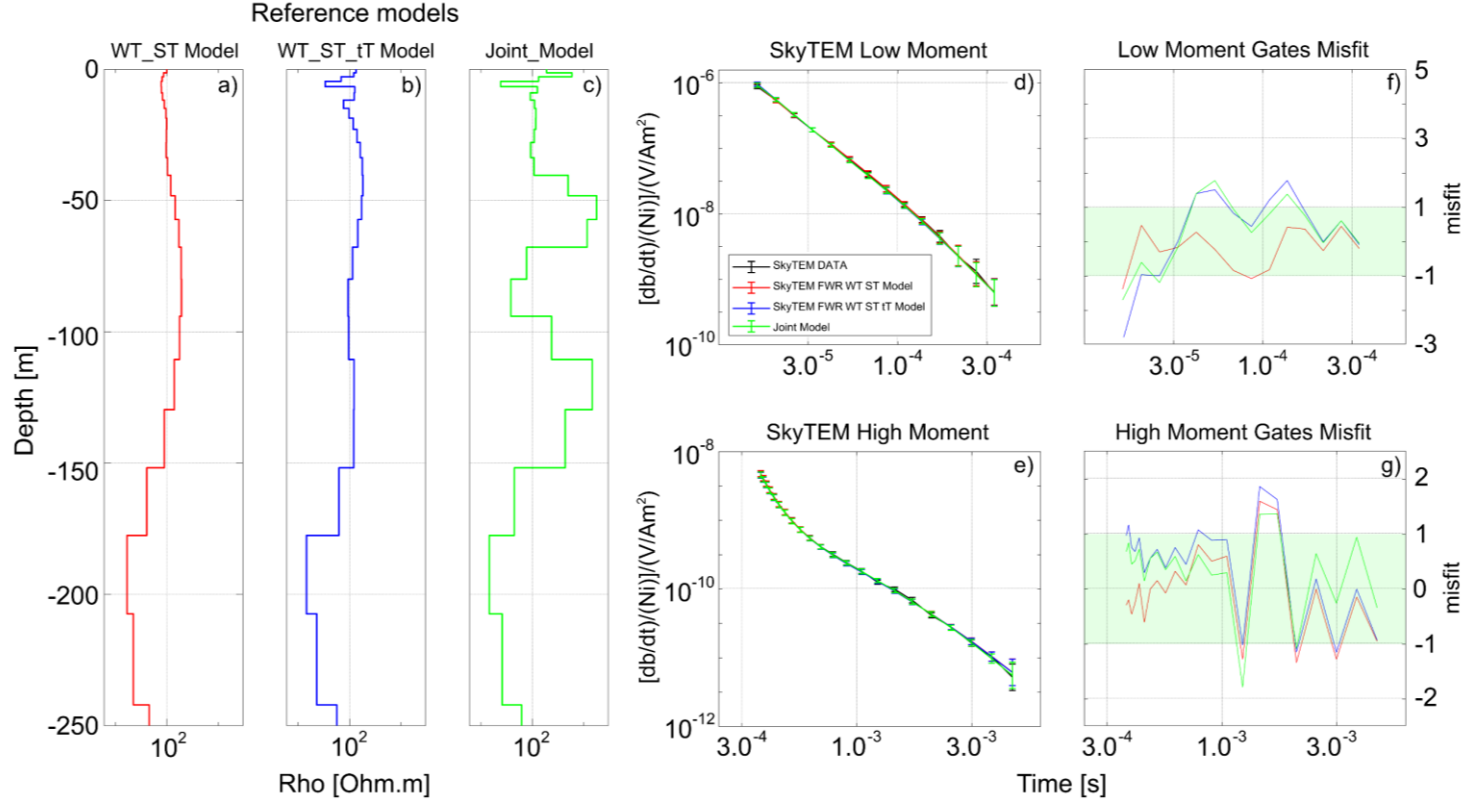


Figure 14: a-b-c) 1D subsoil models used to compute the SkyTEM forward responses, extracted from the inversion of real data. Specifically: (a) Includes ground TEM with a large loop size and airborne EM data. (b) Adds small loop size EM data. (c) Further incorporates galvanic data for full joint inversion. (d-e) Low-moment and high-moment AEM transients computed from the models in the previous panels, shown with the same colour scheme. (f-g) Gate misfit, calculated as $\frac{d_{gate_i} - fwr_{gate_i}}{d_{gate_i} * STD_{gate_i}}$, where d_{gate_i} is the observed data value at the i-th gate, fwr_{gate_i} is the forward response value computed for the same gate and STD_{gate_i} is the standard deviation. For all gates across the transients, the STD is set equal to that of the measured data (black line).

From this figure, it is evident that the three signals calculated for the AEM system led to an equivalence problem. Given this, it makes sense to use the higher-resolution model instead of those with lower resolution, if it comes at no additional misfit cost. On this regard, Figure 14f shows slightly higher misfit values for the forward response computed using the joint model (green lines) compared to that derived from the large-coil EM systems (WT_ST, red lines) only. However, this increase in misfit is not due to the inclusion of the galvanic dataset but rather to the inability to fit both large- and small-coil EM systems equally well using the model that included only EM systems with different coil sizes. This point is demonstrated by presenting the results of forward responses computed using the model derived from the combination of the two inductive datasets alone. (Figure 14b).

Summarizing some key points along the analysis of Figure 14:

- Assessing misfit changes (in this case, a worsening) moving from independently derived models to joint inversion models cannot rely solely on the overall misfit value or on a rule of thumb. Instead, the assessment should focus on:
 - i) how the misfit is distributed across different data types and whether any systematic misfit patterns are present within each data type;
 - ii) whether the worsening is due to the inclusion of galvanic data, or if it is also present with inductive data alone. See Figure 14, panels f and g.
- The observed misfit worsening in the exercise of Figure 14 is due to the combination of the two EM datasets.
- No additional misfit worsening is observed when the galvanic dataset is included.
- Overall, a 25% increase in misfit is considered (positively) remarkable when moving from independent to joint inversion, especially given the resolution gain and the log validation (Section 1.2.1.4).

Therefore, these considerations on Figure 14 raise broader concerns on the fundamental inconsistency between the EM datasets involved in the inversion, and their inability to be simultaneously fit by a single model. Given that the exercise in Figure 14 is based on real field data and subsurface models derived from actual measurements, the source of this incompatibility must be sought in two main possible causes.

The first can be 3D effects arising from the geological distribution at the site, which may be sensed differently by the two systems (featured by different footprint) and not

modelled properly with the 1D approach of the inversion. This can be related to their significantly different transmitter and receiver coil areas (in this case tTEM and SkyTEM; see section 1.2.1.4 for specs.), leading to variations in the actual subsoil models sampled by the measurements at the same surface location.

Another potential explanation lies in differences in the calibration of the two EM systems, a topic further explored in the next section. EM systems calibrated under varying conditions (including environmental changes at the same site) are likely to exhibit discrepancies in the measured signals due to variations coming from the calibration process itself. Consequently, this example may suggest that none of the inductive systems included in Figure 14 were properly calibrated. The next section will examine how environmental conditions at the time of calibration can influence this aspect and why fully accounting for these differences is crucial to preventing measurement inconsistencies between instruments.

1.3.2 IMPACT OF HYDROGEOLOGICAL AND TEMPERATURE VARIATIONS ON EM SYSTEM CALIBRATION

The previous sections concluded by speculating on the possible reasons why two different EM datasets cannot be equally well fitted in 1D within the same inversion process. As said, this incompatibility could arise from differences in how each system senses the 3D resistivity distribution beneath their respective measurement footprints, given their significantly different coil configurations. However, another contributing factor could be discrepancies—or more precisely, inaccuracies—introduced during calibration, which may have been overlooked.

Regardless of the specific cause in this field study, this observation highlights a crucial aspect of calibration processes. When calibrating an E&EM instrument, it is essential to ensure that the calibration site remains unchanged over time—from one calibration session to the next—maintaining consistent electrical properties. Additionally, any unavoidable variations must be carefully accounted for before performing calibration.

One critical aspect that must remain stable at a calibration site is the saturation level of both shallow and deep aquifers, as well as their respective vadose zones. Variations in saturation within a porous medium can significantly alter its electrical properties, potentially affecting the reference model used for calibration. Seasonal fluctuations, for instance, could introduce variability in the calibration site, impacting the measurements performed by the system under calibration.

The relationship between porosity, water content, and the resistivity of a formation is described by the widely used Archie's laws, first introduced by (Archie, 1942). These laws include one formulation for fully saturated media (Eq. (40)) and another for partially saturated media (Eq. (41)), as might be the case in the vadose zone. In the first law, the electrical conductivity of the saturating fluid (σ_w), is related to the electrical conductivity of the saturated rock ($\sigma_{el[sat]}$) considering also the interconnected porosity of the medium ($\phi = \frac{Volume_{effective}}{Volume_{total}}$). Additionally, the cementation factor (m) accounts for the geometry and connectivity of the pore space.

For partially saturated media, the second Archie's law (Eq. (41)) relates the electrical conductivity of a partially saturated rock ($\sigma_{el[p_sat]}$) to variations in porosity and the

fractional water saturation (S_w^n). Here the saturation exponent (n) accounts for the tortuosity and connectivity of the medium.

$$\phi^{-m} = \frac{\sigma_w}{\sigma_{el[sat]}} \rightarrow \sigma_{el[sat]} = \sigma_w \cdot \phi^m \quad (40)$$

$$\sigma_{el[p_sat]} = \sigma_w \cdot \phi^m \cdot S_w^n \quad (41)$$

However, in this work, we focus on another environmental factor that can significantly affect the calibration of EM systems by altering the electrical property distribution of the subsurface. This is the seasonal atmospheric temperature fluctuations, which can significantly influence subsurface temperature and, in turn, impacting its electrical properties distribution. The effect of these fluctuations can reach depths of several meters depending on subsoil characteristics such as the thermal diffusivity, the lateral heterogeneity and the site climatic location. More specifically, temperature variations induce changes in the electrical conductivity of a geological medium that average around 2% per degree Celsius (Eq. (42), Hayley et al., 2007).

$$\sigma_T = (1 + m(T - T_{25})) \cdot \sigma_{25} \quad (42)$$

Where σ_T and T represent the actual electrical conductivity and temperature of the medium, σ_{25} and T_{25} are the reference EC of the medium and the reference temperature at 25 degrees Celsius, respectively, and m represents the fractional change in EC per degree Celsius.

Therefore, seasonal temperature variations in the subsoil may affect EM measurements collected in different surveys over time, such as during the calibration of new instruments, with a stronger temperature effect in highly conductive sites, as indicated by the previous equations. We conclude this section by emphasizing that the optimal site for performing calibrations should be stable from a hydrogeological point of view and exhibit the highest resistivity possible. This is not only because highly conductive sites are known to hinder instrument issues with high signal levels—whereas during calibration, the goal is to identify all potential instrument problems before releasing it—but also because the more conductive the site, the stronger the seasonal temperature effects in the EM calibration process.

For these reasons, we decided to investigate this effect in greater detail in Section 2.1.3, testing the temperature effects on EM transients collected with different systems, on different subsoil models, and in different seasons (temperature models) with a specific attention to EM calibration procedures. The main concern regarding the EM calibration procedure is that temperature variations could lead to over- or under-compensation of signals calibrated under differing conditions, resulting in erroneous corrections when adjusting the on-site measured signal—seasonally influenced—to the reference response. More broadly, Section 2.1 provides a detailed description of the effect of atmospheric temperature on the electrical properties of the subsoil also through the second scientific paper produced during the Ph.D., which presents a real-data case study to illustrate the extent of temperature-induced variations in ground electrical properties.

Then, with a specific focus on EM system calibration, Section 3.1 presents final considerations and analyses on the effects of atmospheric temperature on EM calibration, introducing different proposals for advancements in EM calibration procedures to specifically address these temperature-related considerations.

1.4 REFERENCE SITES FOR E&EM CAMPAIGNS AND GEOLOGICAL INTERPRETATION

Another essential aspect for the success and completion of a geophysical investigation is the ability to translate the electrical models into meaningful information that accurately reflects subsurface geological units and their hydrogeological, chemical, or mechanical properties. As noted earlier, the E&EM joint inversion allows for a more comprehensive description of the subsurface, producing higher-resolution models (see Section 1.2.1).

E&EM campaigns are often part of broader projects whose goal is to translate geophysical models into geological insights—specifically, by converting electrical parameters into lithostratigraphic information. In this context, the establishment of a reference site can play a crucial role in facilitating this translation process. A reference site is meant to be a location where geophysical models are available at the highest possible resolution, and ideally where borehole data—including both lithological description and geophysical logs—are also available. This setup enables a direct one-to-one correlation between geophysical models and lithology, which can then be extended to other areas within the

same geological setting, such as those covered by the broader AEM campaign. Given the importance of achieving the highest resolution at the reference site, its characterization through the joint inversion approach is particularly advantageous, enabling a new level of interpretation and geological understanding. In the following sections, we propose advancements in the establishment of such reference sites and, more broadly, in refining the translation of geophysical models into geology, also in the case where the reference site is meant to support an AEM project.

1.4.1 THE HYDROGEOSITE REFERENCE SITE

The initial application of the joint-approach for establishing geophysical reference sites stemmed from the execution of an Airborne ElectroMagnetic (AEM) campaign conducted in northern Italy. This campaign, the most extensive AEM survey in Italy to date, spanned over 1800 km² within an area (Figure 15) featured by complex geology characterized by the presence of fluvioglacial and glacial deposits. These deposits, largely formed during glacial and interglacial periods, are characterized by complex near-surface sedimentary arrangements where moraine and fluvial deposits form patterns of superimposition and interdigitation. The primary objective of the AEM campaign was to capture a detailed characterization of both shallow and deep groundwater systems to provide new extensive and accurate information descriptive of the hydrogeological framework. Therefore, the campaign aimed to provide support for the regional water-resource management, allowing the definition of present and future strategic planning.

As previously discussed, properly interpreting the geophysical models—now specifically translating them into hydrogeological information for the area—is crucial to achieving the campaign objectives.

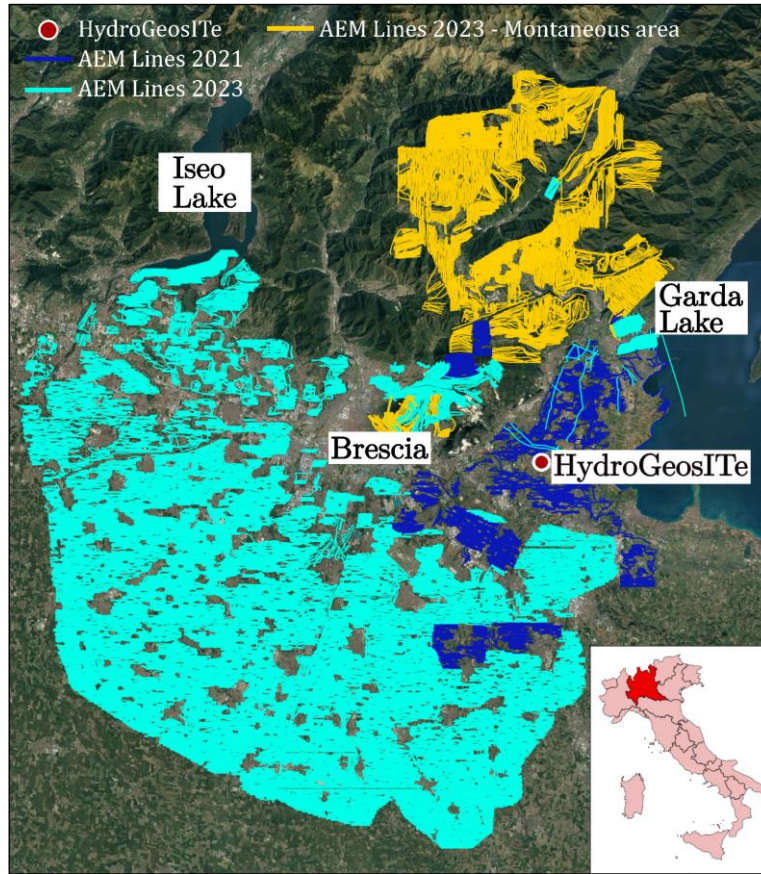


Figure 15: Airborne EM survey lines acquired in 2021 (dark blue and ochre lines) and in 2023 (cyan lines) as part of the largest AEM campaign ever conducted in Italy. The reference site for the campaign, the HydroGeosITe, is indicated by the red dot.

In the case of this AEM campaign, the reference site, designated HydroGeosITe, was characterized starting from the joint inversion results outlined in Section 1.2.1.4. There, we initially presented the 2D models produced for the site, even though the data coverage shown in Figure 6 clearly reveal a high-density 3D E&EM data coverage. This extensive data acquisition was deliberately designed to create a comprehensive reference site for this AEM campaign. The goal of the campaign was to characterize the hydrogeological structures across the AEM-surveyed areas, which display both regionally extensive features along with short-wavelength lateral and vertical heterogeneities. The latter complexity can only be fully appreciated by downscaling the analysis to specific sites like the HydroGeosITe, where the ground follow-up enables the detail study of the spatial variability. The three-dimensional data-characterization is intended to capture the geometry of the hydrostratigraphic bodies, expected to significantly influence groundwater flow dynamics. Furthermore, studying these structures geometrically can

facilitate lithostratigraphic unit associations that would not be feasible with point-based data alone, such as data from boreholes.

In addition to its interpretative-reference value, the HydroGeosITe has practical strategic importance, as multiple boreholes are planned to be drilled to access the deep groundwater resources of the area. At the time of the present work, one borehole has already been completed to a depth of -208 meters from the surface (Figure 16) and used also to validate the joint geophysical model presented in Section 1.2.1.4. This borehole, which includes detailed lithological descriptions and geophysical logEM measurement, supports the translation of the electrical resistivity model into lithostratigraphic information, further enhancing the interpretive value of the site.

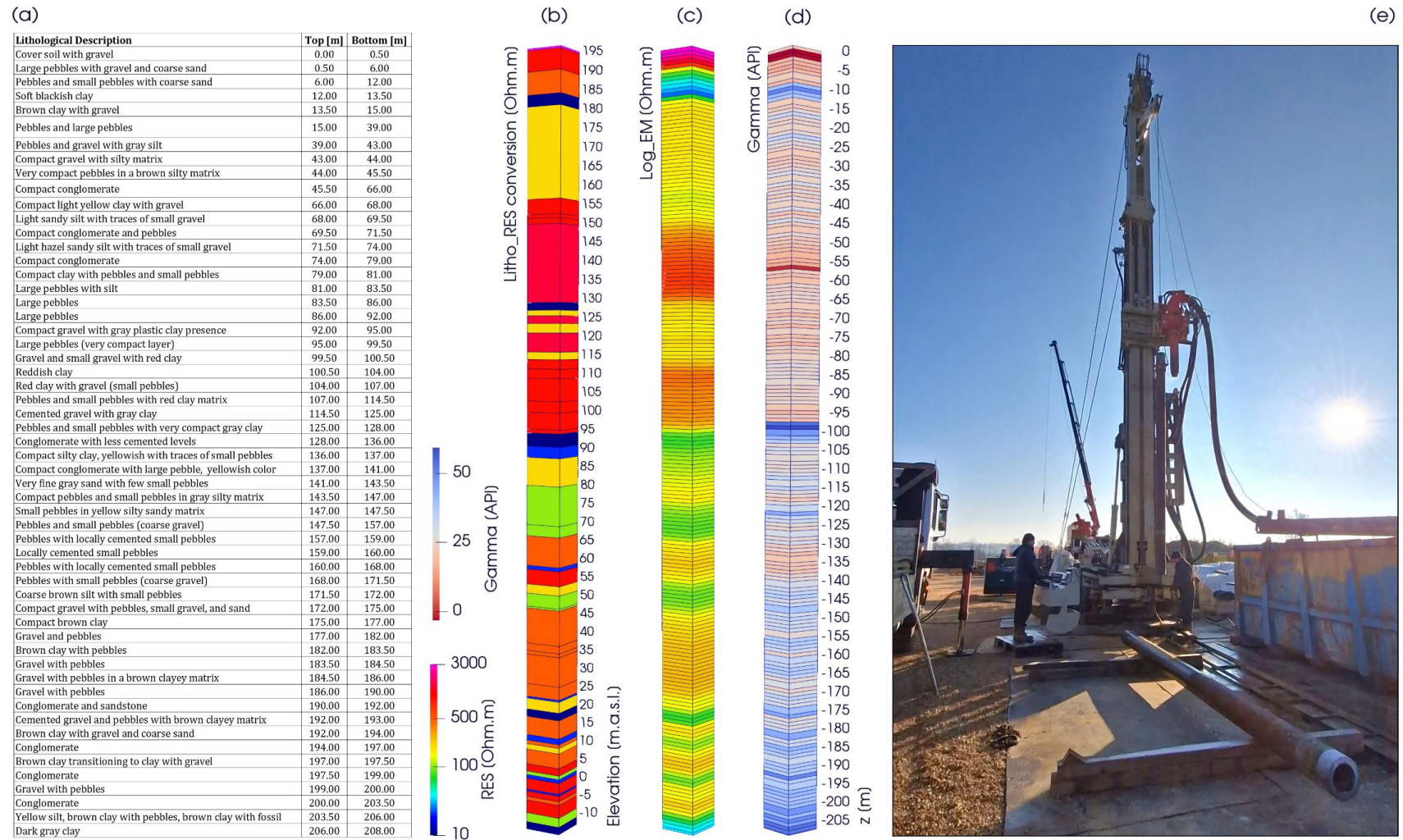


Figure 16: a) Description of the Litho-stratigraphical units observed in the borehole, including the top and bottom depths of each unit. The elevation of the top stratigraphic unit is 197 m.a.s.l. b) Association of the litho-stratigraphic units with electrical resistivity values, based on the comparison with the logEM measurements. c) Results of the log-EM measurements conducted in the borehole. d) Results of the Gamma measurements conducted in the borehole. e) Picture depicting a phase of drilling operations.

1.4.1.1 3D migration of the joint inversion

To assess the spatial continuity and persistence of hydrogeological features at the HydroGeosITe, the entire area has been thoroughly covered with high-productivity EM measurements (Figure 17a), with in over 55 km of tTEM data, where approximately one EM sounding every ten meters is collected, each reaching depths of 110-120 meters ca. Additionally, to explore the deeper hydrogeological portions, high electromagnetic-moment measurements were conducted, extending beyond the lower limits of the previously obtained models (Figure 17a, see also Figure 13a for the transients). Five 100x100 m transmitter areas measurements were acquired with 60 minutes of stacking time and 30 ms of acquisition time, alongside one 200x200 m transmitter area measurement, where 100 minutes of stacking were collected with 30 ms of acquisition time.

As shown in Figure 17a, the galvanic and inductive data coverage does not uniformly overlap across the entire site, primarily due to the different logistics associated with each survey method. Despite these differences, the goal for this section is to extend the high-resolution 2D joint inversion model by applying inversion migration techniques. This approach aims to transfer the detailed joint-inversion information to the lateral areas of the 3D model where the galvanic data coverage is absent. The inversion setup for this approach incorporates most of the available data (excluding the deep ground TEM data, which will be addressed separately) within a modeling framework that includes all the joint-profiles as prior information. Specifically, a multi-cycle strategy (see Section 1.2) was employed, beginning with an initial inversion cycle to propagate the high-resolution information from the central profiles enforcing lateral constraints to produce a horizontal interpolation. The resulting 3D model from this preliminary cycle serves as the starting model for the next inversion cycle, where it is integrated as prior information in the model update equation with a uniform standard deviation of 5% applied across the 3D space. Within this subsequent cycle, both tTEM and SkyTEM data are incorporated, with disentangled 1D forward meshes used to calculate forward responses for each dataset. Strong spatial constraints are applied to ensure that the information in the central regions effectively migrates across the model, enhancing the final resolution of the whole 3D resistivity model.

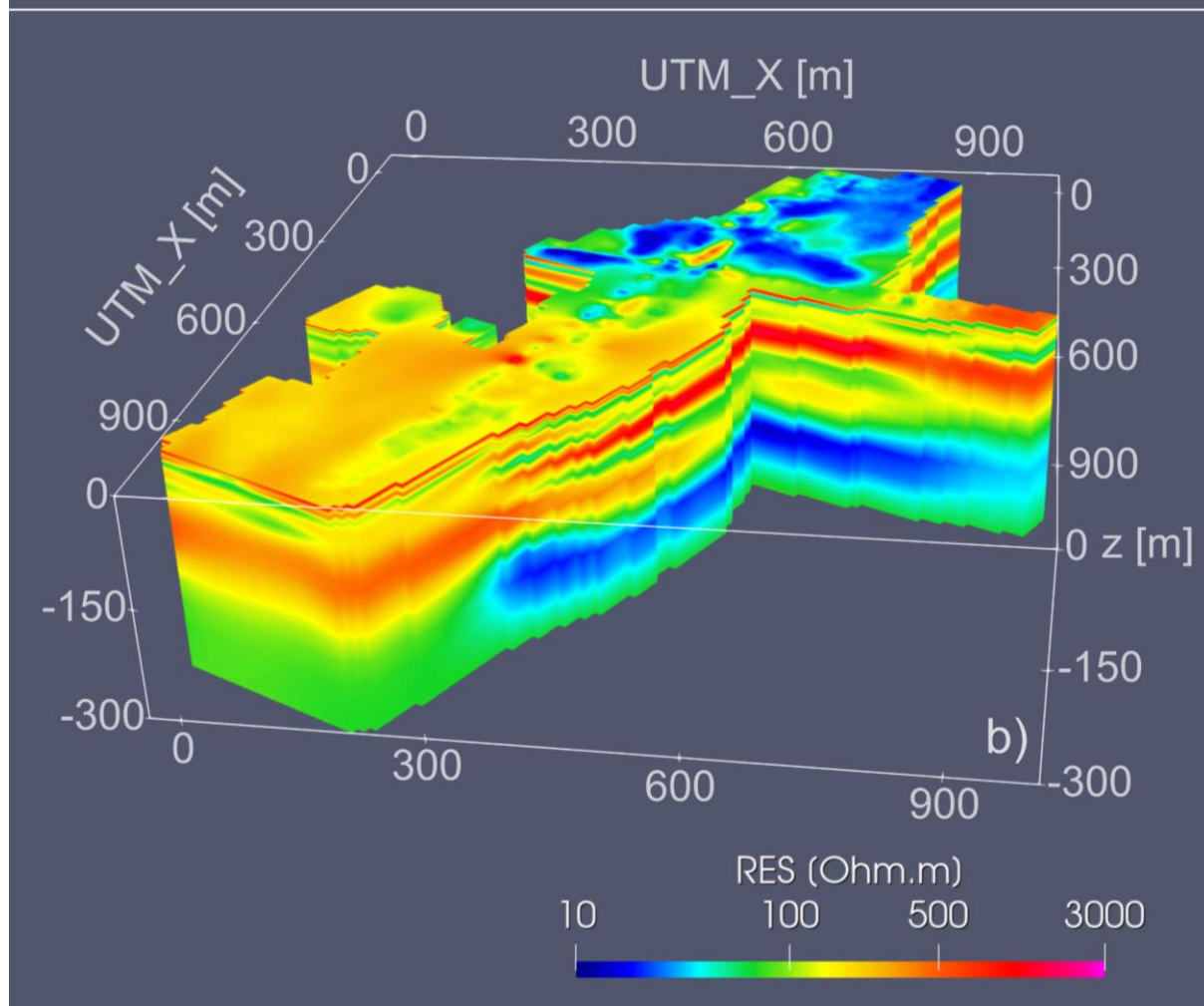
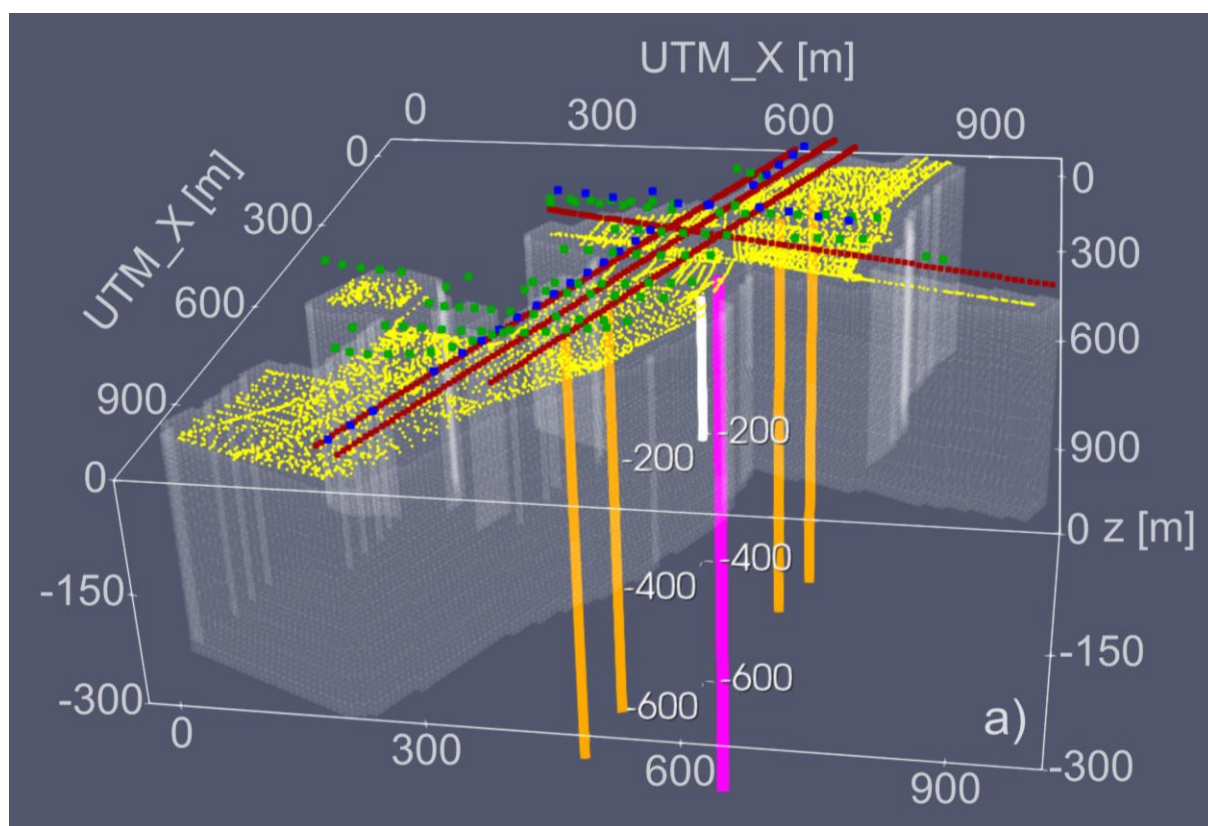


Figure 17: a) Data coverage for the site of interest includes red in-line dots representing the four galvanic DCIP profiles, green dots indicating the locations of inductive AEM soundings, and blue dots showing the ground EM soundings with 40x40 meter transmitter areas. The orange vertical polygon marks the location and depth of the ground EM sounding with a 100x100 meter transmitter area; the magenta one represents the 200x200 meter sounding, which also corresponds to the location of one 100x100 meter measurement. Yellow dots indicate the tTEM EM soundings, completing the 3D data coverage of the site, and the white vertical polygon marks the borehole locations. b) Three-dimensional model obtained through inversion, incorporating the joint profiles as prior information alongside the extensive 3D EM data coverage.

The results of this approach are presented in Figure 17b and in the slices of Figure 18, where the strong resistivity contrasts across the three-dimensional model are visible at most depths. This indicates that the information from the joint profiles successfully migrated throughout the model, substantially enhancing resolution compared to the inductive-only model (Figure 19). Figure 18 and 20 further illustrate these improvements, comparing slices from the 3D prior-joint inversion model with those from the tTEM-only inversion model respectively. Table 6 reports the misfit values for the 3D-volume inversions conducted using the tTEM dataset alone and the combined tTEM, AEM, and prior information. These results indicate a satisfactory misfit for the tTEM dataset in the Joint 3D inversion, while the higher misfit in the SkyTEM data confirms challenges in perfectly fitting the two datasets together, as previously discussed in Section 1.3.1 (refer to Figure 14). However, the significantly higher resolution of the 3D model remains supported by the comparison with the borehole logEM measurements, as presented in the following.

Table 6: Misfit values for the independent and the joint-prior inversion datasets.

MISFIT	tTEM	SkyTEM	Prior
Independent Inductive inversion (tTEM only)	0.56	/	/
Joint 3D	0.91	2.12	1.6

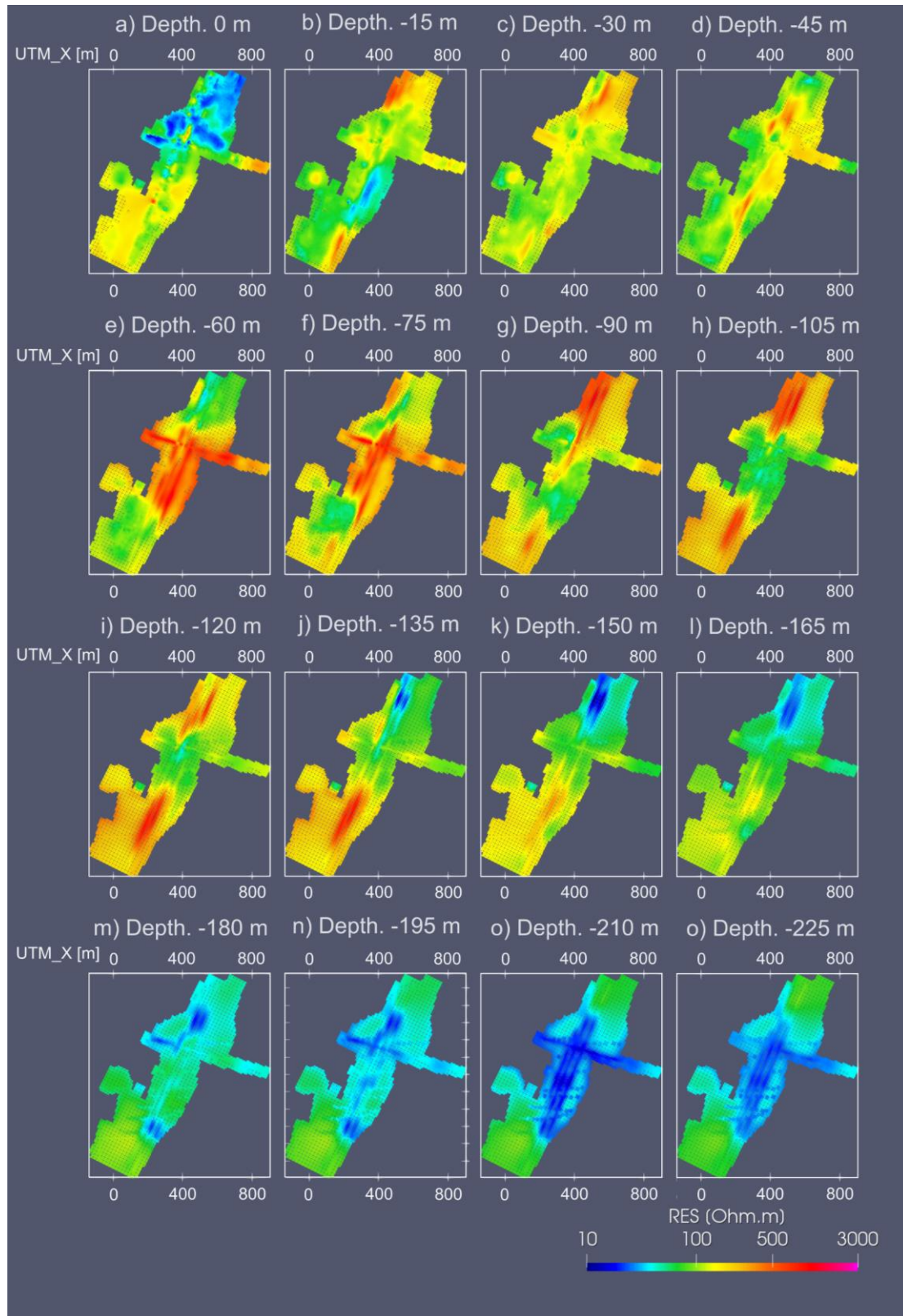


Figure 18: Depth Slices of the Three-dimensional model obtained through inversion, incorporating the joint profiles as prior information alongside the extensive 3D EM data coverage. The portions of the model below the DOI are indicated with a dotted pattern.

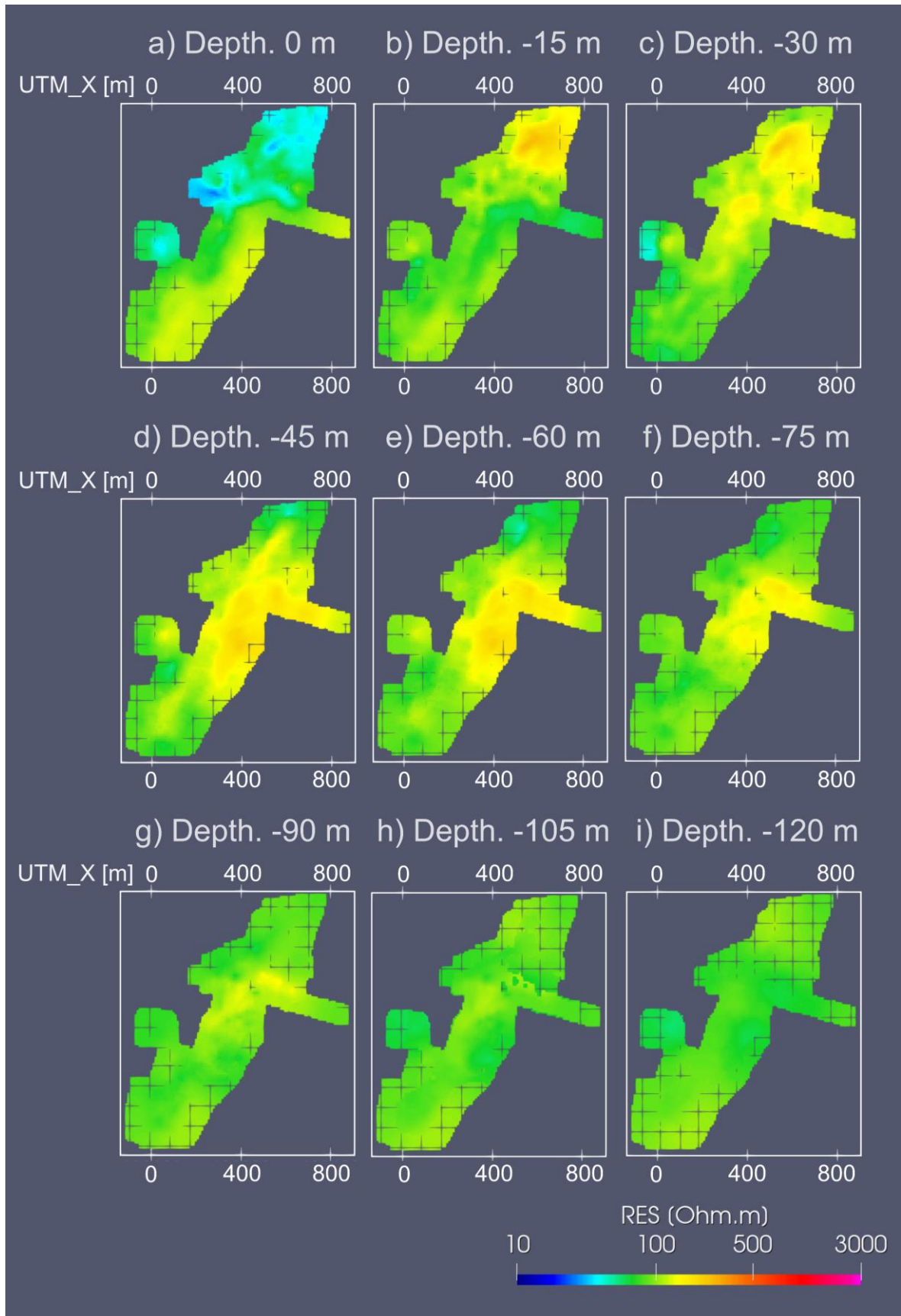


Figure 19: Depth Slices of the tTEM model. The portions of the model below the DOI are indicated with a line pattern.

These three-dimensional results now allow for the study of the subsurface spatial architecture by isolating specific resistivity intervals likely representing the lithostratigraphic units introduced in Figure 16a. This approach goes beyond the borehole point data or the 2D profiles interpretations, extending the information across the entire area while maintaining high resolution features. In Figure 20, specific resistivity intervals are extracted to isolate volumes that are likely to correspond to distinct lithostratigraphic units or specific hydrogeological conditions. Figure 20a focuses on resistivity values lower than 100 Ohm·m at depths shallower than 40 meters from the surface, highlighting volumes that may contain materials ranging from clay-rich deposits to cohesive sediments. Figure 20b emphasizes the high-resistivity parts of the volume, isolating areas with values greater than 300 Ohm·m. This reveals an irregularly shaped body with resistivity exceeding 1000 Ohm·m, interpreted as the stony conglomerate reported for this area and known for displaying varying degrees of fracturing. At greater depths, below 100 meters, volumes with resistivity below 40 Ohm·m are isolated, exposing the 3D structure of an underlying marine clay layer, which is known in the region to act as a boundary between the fluvio-glacial deposits above and the marine sequence below.

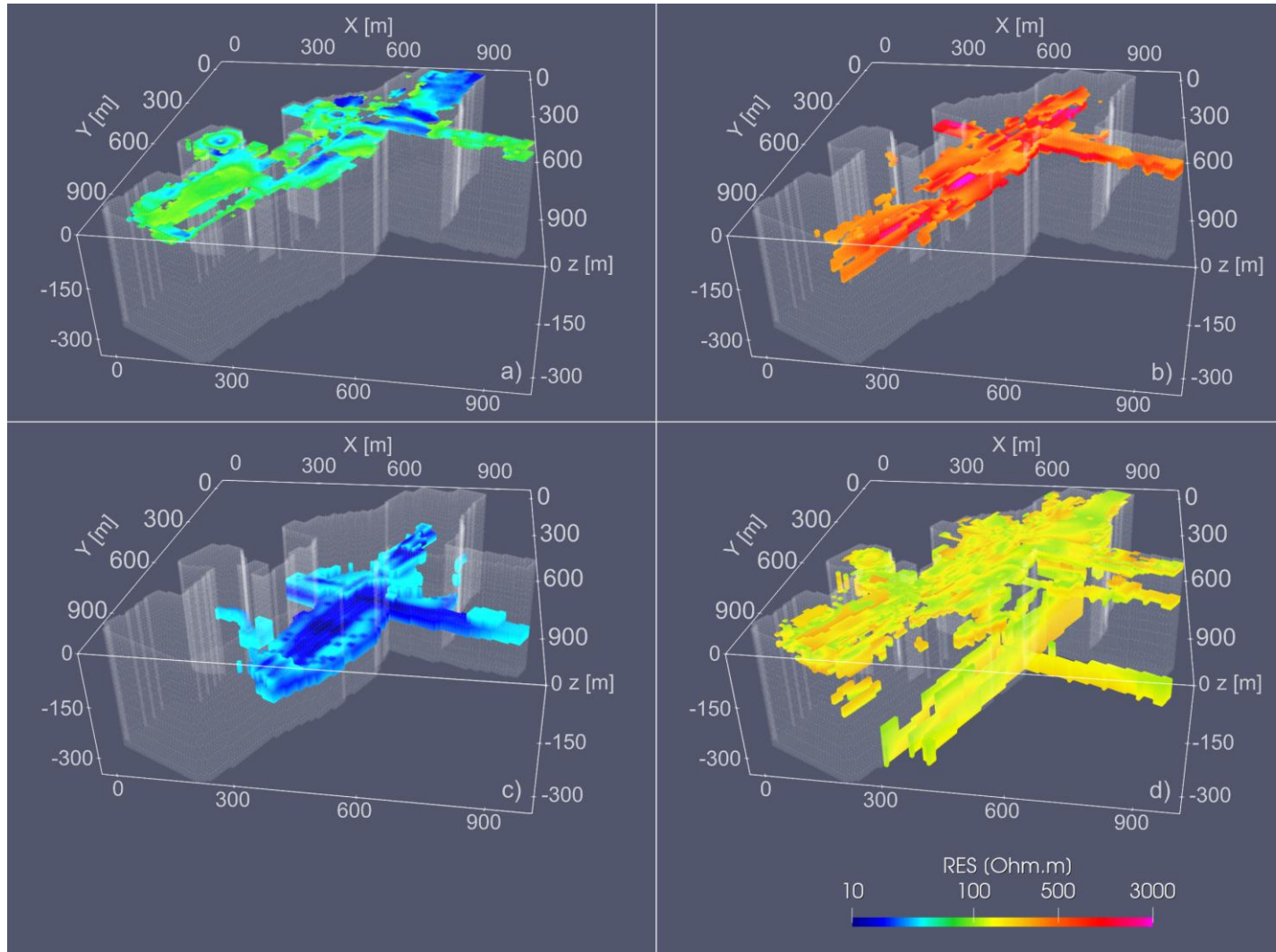


Figure 20: Resistivity volumes extracted from the inversion employing 3D distributed EM soundings and fixing the joint inversion models as prior information. a) Resistivity volumes reporting values up to 100 Ohm.m and shallower than 40 meters of depth. b) Resistivity volumes reporting values higher than 300 Ohm.m. c) Resistivity volumes reporting values lower than 40 Ohm.m and with depth greater than 100 Ohm.m. d) Resistivity volumes values between 100 and 300 Ohm, extracted for the whole depth of the model.

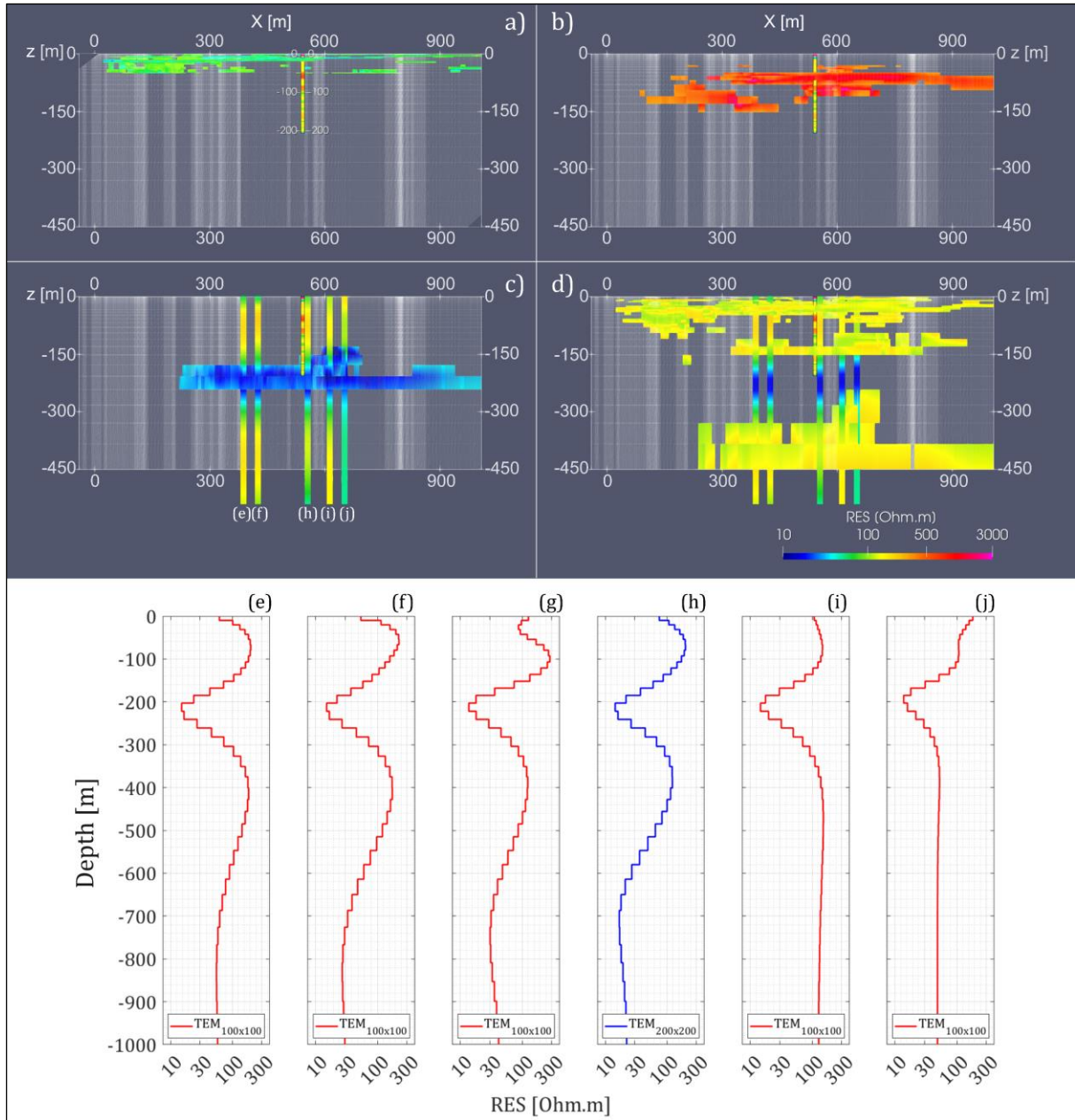


Figure 21: a-d) Resistivity volumes extracted from the 3D inversion model as described in the previous figure. In the upper panels (a-d) the borehole log-EM is reported along with the deep TEM 1D models (only in panels c and d). e-j) 1D deep TEM models. Refer to panel c for their spatial positioning. Plots g and h report respectively the 100x100m and the 200x200 meters transmitter measurements acquired in a coincident location.

To establish the reference site with a focus on hydrogeological features, it is crucial to first delineate the hydro-architecture within the fluvio-glacial compartment and then extend the analysis to the deeper marine sequence. Starting with the upper fluvio-glacial section, Figure 20d focuses on resistivity values between 100 and 300 Ohm·m, aiming to isolate

the granular bodies, which are likely to host groundwater or represent permeable horizons that could influence groundwater flow. Two main horizons with these characteristics are identified within the first 200 meters of depth and are clearly visible also in the upper part of Figure 21, panel d. The first horizon, located between 20 and 60 meters below the surface, likely functions as an aquifer, a conclusion further supported by the analysis of the complex conductivity section for this depth interval in Figure 12, where low chargeability features are observed. Moving deeper, a second layer with aquifer-compatible resistivity values is found between 100 and 150 meters depth, within a depth interval where resistivity values compatible with the stony-conglomerate unit are also observed laterally. The latter represents an important hydrogeological feature in the area, exhibiting a wide range of hydraulic behaviors depending on the degree of fracturing. Greater fracturing imparts porous characteristics to the unit, enhancing its ability to store water. The compactness of this unit varies across the site, degrading into gravel-like material that could be challenging to distinguish through borehole analysis alone. In fact, this creates difficulties in differentiating between gravel deposits formed through different sedimentary processes and conglomerate-derived gravel, where incomplete lithification or disaggregation has contributed to its granular nature. Recognizing this transition from conglomerate to gravel requires a spatial analysis and evaluation of the lateral continuity and evolution of the deposits—an often difficult task when relying solely on localized data sources.

Figure 22a isolates the high-resistivity features in the 3D model between 60 and 200 meters depth. Notably, moving from south to north in the model (left to right in Figure 22a), it is possible to observe a seamless transition from high-resistivity conglomerate-like values (red) to gravel-like resistivity values (orange-yellow), suggesting a lithological evolution within the unit. As this transition is followed towards the borehole location, it becomes evident that the borehole intersects this unit at two different depths, with varying degrees of consolidation. The first intersection, at a shallower depth (around 50 to 80 meters), exhibits very high resistivity values, corresponding to compact conglomerate, as noted in the lithological description (Figure 16a). Moving deeper, the borehole reaches a zone where the resistivity values suggest a fractured, gravel-like deposit (Figure 22a), which is corroborated by the driller lithological description at around 150 meters depth. Here, the deposit contains pebbles of various sizes with varying

degrees of compactness and sporadic matrix presence. Interestingly, following this horizon towards the south (left side of Figure 22a), the transition from gravel-like resistivity values to higher values can be observed, suggesting the lateral transition in compact conglomerate. It is worth noting that the borehole lithological description at around 150 meters depth does not associate the core samples with any conglomeratic origin, highlighting the challenge of unambiguously linking certain deposits to lithostratigraphic units based solely on isolated borehole data. This underscores even more the value of the spatial analysis, which enables geometric elements for interpreting the stratigraphic units.

Moving now to the deeper sections of the site (depths exceeding 200 meters), an additional objective of this campaign for establishing the reference site, was to characterize the largely unknown hydrogeological features of the underlying marine sequence, seeking groundwater resources to exploit. Figure 21d and Figure 22b display the portions of the 3D model below 200 meters, where resistivity values indicative of potential aquifers are isolated, suggesting the presence of an extensive and continuous anomaly beneath the overlying marine clay. It is important to note that the depth of investigation (DOI) for the 3D model ends within the upper layers of the marine clay in most areas. To further investigate and validate these deeper parts, the ground-based TEM surveys with large transmitter areas were employed (see Figure 17a). The 1D inversion results from the 100x100 meter and 200x200 meter transmitter areas are presented in Figure 21e-j. This analysis shows the continuity of a low electrical resistivity anomaly between 200 and 250 meters of depth, followed at greater depth by a notable increase in resistivity, compatible with aquifer resistivity values. When overlapping the 1D deep TEM models with the deep-marine clay volumes (Figure 22b), a strong spatial correlation emerges first with the high conductivity volume, then with the higher resistivity volumes. It is important to mention that the large transmitter TEM data was not included in the 3D inversion dataset. The correspondence between the models is seen as a validation of the deep high-resistivity anomaly.

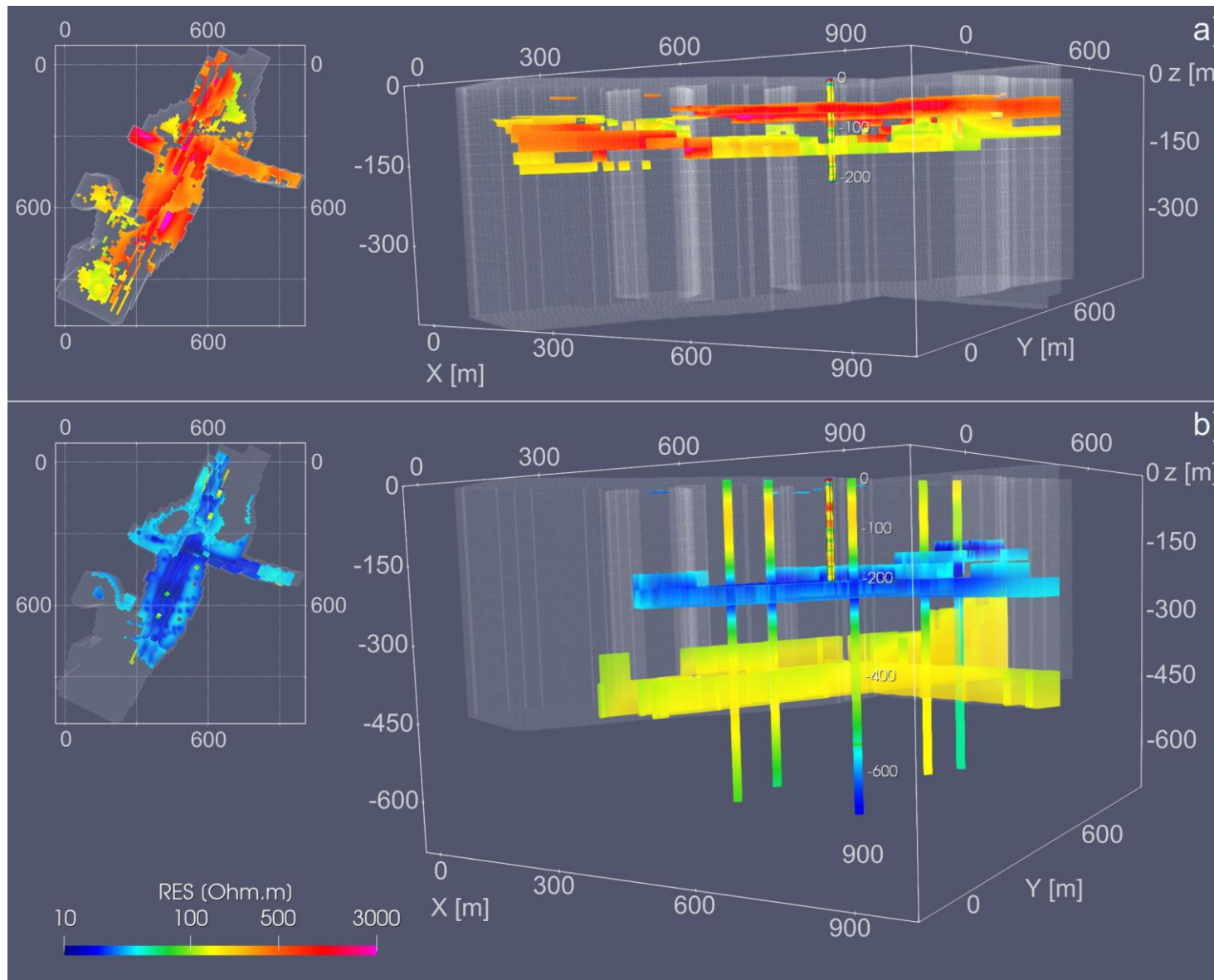


Figure 22: a) Resistivity features higher than 300 Ohm.m in the 3D model between 60 and 200 meters of depth. b) Main resistivity features below 200 m, within the marine depositional unit. Both the volumes extracted from the 3D model and the deep-TEM 1D models are reported. The log-EM measurements and the plan view of the volumes are reported along.

The results presented above are considered to demonstrate the success of the new procedure in establishing the reference site for E&EM campaigns, advancing the state of the art in the translation from geophysical to geological information. This approach ensures the highest resolution while minimizing sensitivity bias of the E&EM systems to the subsoil resistivity distribution. Concurrently, the possibility to extend these investigation improvements to the three-dimensional space allows the geophysical interpretation of the geological features to be performed also by approaching the identification of the geological units with geometrical analysis, representing a direct connection point between geophysics and lithological sides.

Besides the advantages of having a high-resolution 3D model for establishing a reference site, such spatially detailed models can also offer significant benefits when infrastructure facilities are planned for construction on the site. For instance, at the HydroGeosITe, a borehole is planned to be drilled to explore the deepest portions of the site in search of deep groundwater resources. In this case, the drilling location can be optimized by targeting areas in the models where resistivity anomalies suggest the presence of water-bearing units with favourable storage characteristics. At the same time, it is beneficial to avoid regions where conglomerate units appear highly lithified, thus reducing operational costs and improving drilling efficiency.

This consideration represents a first example of how ground-based geophysics can be used as a follow-up to support, for instance, AEM campaigns in areas where higher resolution is needed for engineering planning. A specific example of this is presented in the next section.

1.4.2 JOINT INVERSION FOR GEOLOGICAL INTERPRETATION AT FOLLOW-UP SITES

In the previous section, we discussed the need to establish reference sites to translate resistivity AEM models into accurate lithostratigraphic interpretations. As noted, AEM campaigns produce large-scale models that provide a broad overview of the main geological structures in the area, enabling the identification of suitable locations for implementing specific structures. However, these models often lack the resolution required for detailed on-field implementation planning. To address this, ground-based

follow-up using instruments with higher shallow resolution can target specific locations and improve the future project planning.

In this context, joint inversion can still play a key role in achieving the required resolution for subsoil characterization. This chapter explores its application in studying a site that demands high-resolution subsoil descriptions since it was designated for aquifer artificial recharge experiments. In this case, AEM data could not be acquired due to logistical challenges, as the area was highly urbanized and inaccessible by helicopter. Moreover, even if AEM models had been available, they would likely have been too smoothed for this purpose.

Specifically, for the E&EM acquisition at the site, 15 profiles of galvanic DCIP data were collected using the Terrameter LS2 instrument (Figure 23, red dots). Each profile was 300 meters long and acquired using a gradient array with electrodes spaced 5 meters apart resulting approximately in 12000 measured quadrupoles across the area. The mean injected current for each quadrupole was 0.5 amps. The data acquisition employed a 100% duty cycle energizing scheme (Olsson et al., 2015) with 4 kHz full-waveform sampling, and the IP measurement window extending up to 6 seconds of active acquisition. Purposefully for the joint investigation, inductive measurements with the tTEM system (Auken et al., 2019, see Section 1.2.1.4) were first collected along the galvanic profiles and then extended to fill the spaces in between (Figure 23, blue dots). Approximately 2000 EM soundings were acquired for the area.

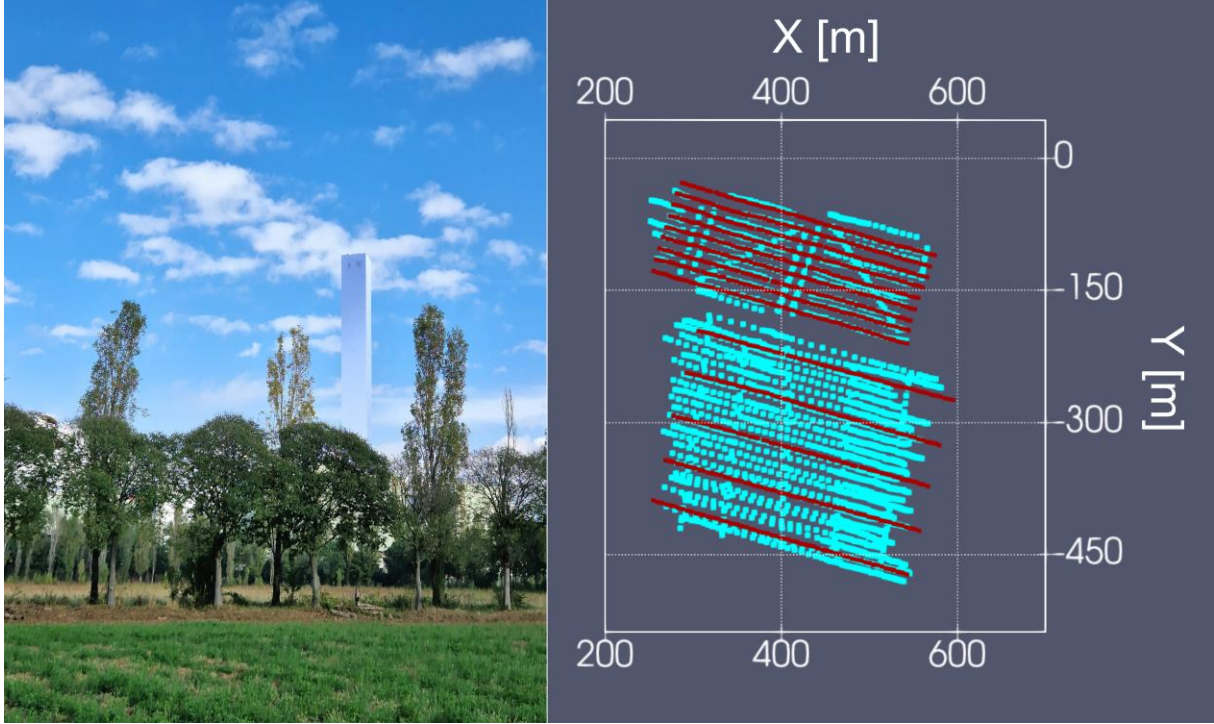


Figure 23: Geophysical coverage at the site designated for artificial recharge experiments. The red dotted line represents 15 overlapping galvanic DCIP profiles, while light blue dots indicate acquired EM soundings overlapping those lines and filling the gaps.

The acquired data underwent the same approach described in Section 1.2.1.4, beginning with the accurate processing of all inductive and galvanic datasets. This was followed by the independent modelling of the data and subsequently the application of the joint modelling framework.

The modelling approach follows the strategy outlined in Section 1.2.1.3, using 1D forward responses for the EM datasets and 2D for the galvanic data. The key difference in modelling the data acquired at this site is that, for both independent and joint models, inter-model constraints were enforced alongside the standard intra-model regularization. This approach was designed to promote consistency among the models and achieved by incorporating the data into a unified inversion framework. Within this framework, independent model meshes were defined for each profile and then connected through constraints. These constraints not only encouraged similarity among the models but also expanded the data space, thereby promoting data-driven solutions across the profiles while preserving differences when present in the data. Regarding the inter-model regularization, the strength of the horizontal constraints has been doubled moving from joint to independent inversion.

Figure 24 presents the independent and joint models obtained for the 15 profiles measured. Figure 24a shows the inductive tTEM models, inverted using the same model discretization defined for the galvanic models (Figure 24b), which was subsequently extended to the joint models (Figure 24c). All models are cropped according to their respective depths of investigation (DOI). Whereas the inductive, galvanic, and joint models are compatible, they reveal differences in representing the subsurface structure and absolute resistivity values, similar to the observations in Section 1.2.1.4. The inductive models are more effective at depicting the low-resistivity features of the subsurface, whereas the galvanic models better capture high-resistivity features, both coherently with their different sensitivities. The joint models prove enhanced resolution successfully resolving the low-resistivity features depicted by the inductive data along with the high-resistivity features brought by the galvanic data. This improvement is due to the balanced integration of the different sensitivities of the methods. As a result, the joint inversion not only enhance the depiction of absolute resistivity values but also slightly differ in the spatial relationships between resistivity features.

Regarding the data fitting, Table 7 reports the misfit values obtained for each dataset included in the independent inductive and galvanic inversions, as well as in the joint inversion framework. Overall, the results demonstrate a good data fit across all models and modelling frameworks. Notably, the joint inversion achieves a data misfit comparable to the independent inversions, with a slight worsening of the inductive data fit. However, this remains well within the acceptable range. For the galvanic data, the joint inversion exhibits variable behaviour, frequently showing an improvement in data fitting compared to the independent inversions. The noise characteristics of the site are well reflected in the misfit distribution. Specifically, the most noise portions, caused by the presence of anthropic infrastructure, are concentrated at the borders of the acquisition area.

Table 7: Misfit values for the 15 inverted profiles, corresponding to the inductive tTEM inversions (second column), galvanic DCIP inversions (third column), and joint inversions (fourth and fifth columns). The number of EM soundings and the measuring electrodes used for each profile are specified in round brackets.

	tTEM (n. soundings)	DC/IP (n. quads.)	JOINT	
			tTEM	DC/IP
P1	1.1 (45)	2.0/1.7 (771)	1.4	1.4/1.6
P2	0.9 (142)	1.6/1.5 (305)	1.2	1.4/1.5
P3	1.0 (167)	1.9/1.6 (794)	1.2	1.6/1.6
P4	0.7 (331)	1.8/1.6 (614)	0.8	1.4/1.5
P5	0.7 (492)	1.8/1.8 (796)	0.8	1.5/1.8
P6	0.7 (705)	2.0/1.7 (784)	0.8	1.9/1.7
P7	0.7 (598)	3.2/1.9 (746)	0.8	3.0/1.9
P8	0.6 (563)	2.0/2.0 (777)	0.9	2.0/1.9
P9	0.6 (725)	2.1/1.3 (714)	0.8	2.0/1.3
P10	0.5 (610)	2.4/1.4 (811)	0.8	2.0/1.3
P11	0.4 (834)	2.2/1.5 (817)	0.7	2.5/1.5
P12	0.3 (734)	1.8/1.6 (813)	0.8	1.9/1.6
P13	0.4 (607)	1.7/1.4 (811)	0.8	1.8/1.4
P14	0.5 (580)	1.5/1.5 (806)	1.0	1.6/1.5
P15	0.5 (477)	1.3/1.5 (813)	0.9	1.3/1.5

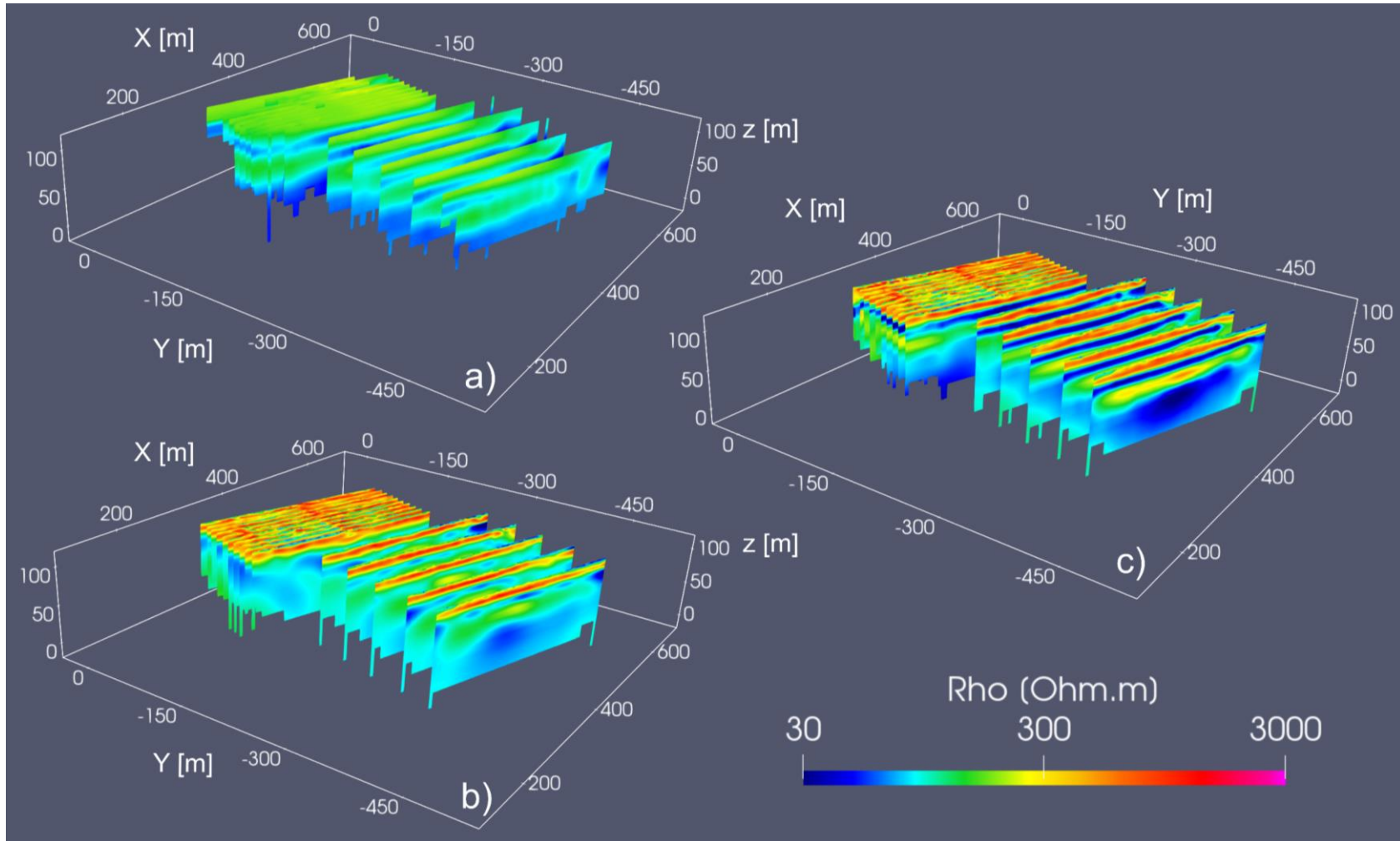


Figure 24: Inversion models for the site were carried out along the galvanic line tracks, including the acquired EM data. (a) tTEM inductive models, (b) galvanic models, and (c) joint models obtained by unifying the data space to incorporate both datasets. All models are cropped over the DOI.

Figure 25 aim first at showing in detail the differences described between the independent and joint models and then to propose the validation of the obtained results by including in the analysis a borehole that provided lithological description.

Figure 25 presents the P12 inductive (panel a), galvanic (panel b), and joint (panel c) models, highlighting the different capabilities of the methods in depicting resistivity anomalies in the subsurface. The joint model (panel c) stands out by displaying a broader resistivity range compared to the individual inductive and galvanic models. Notably, the joint model pinpoints the first low-resistivity anomaly (around 95 m.a.s.l., panel c) slightly deeper compared to the inductive model. Furthermore, it significantly sharpens the boundaries of the high-resistivity feature at around 80 m.a.s.l (panel c), redefining its lower limit redefined compared to the galvanic model. To validate the models, a borehole is overlaid by projecting it from its original location, approximately 1 km far from the centre of the profile, and

reaching a depth of around 165 meters (borehole data extracted from the geological portal of this region: <https://www.datigeologicisottosuolo.servizirl.it/viewer/>; ID: 17466; WGS84_UTM32: 594860.2, 5040929.4). The lithostratigraphic alternation is

Table 8: Thicknesses, simplified lithological description and proposed resistivity values for the conversion of the borehole information shown in Figure 25a-c.

Thickness [m]	Litho. Description	
16	Sand_01	Red
10	Clay	Dark Blue
24.0	Gravel and Pebbles	Yellow
5.0	Clay	Dark Blue
7.0	Gravel and Pebbles	Yellow
1.0	Silt	Dark Blue
7.0	Clay	Dark Blue
10.0	Conglomerate	Orange
5.0	Clay	Dark Blue
10.5	Silt	Dark Blue
1.0	Clay	Dark Blue
3.5	Gravel and silt	Light Green
10.0	Sand_02	Light Green
4.0	Clay	Dark Blue
6.0	Silt	Dark Blue
5.0	Clay	Dark Blue
3.5	Gravel and Pebbles	Yellow
8.5	Gravel and Silt	Light Green
5.5	Sand_03	Light Green
4.5	Gravel and Pebbles	Yellow
17.5	Clay	Dark Blue

detailed in Table 8 which reports a simplified description compared to the one can be accessible at the previous site. In the same table are also reported the borehole colours used in Figure 25, in which moving from warm to cold colours reflect an increase in the fine-cohesive fraction. The comparison between the borehole and the geophysical models (Figure 25a-c) shows overall good agreement across all models, thereby validating the geophysical results. Notably, the joint model outperforms the independent models in depicting the geological architecture within the first 70 meters of depth. To further illustrate the differences between the independent and joint modelling approaches, Figure 25d-f presents the 1D models extracted at the location where the borehole has been projected. These comparisons highlight the sharper resolution of electrical anomalies achieved by the joint model.

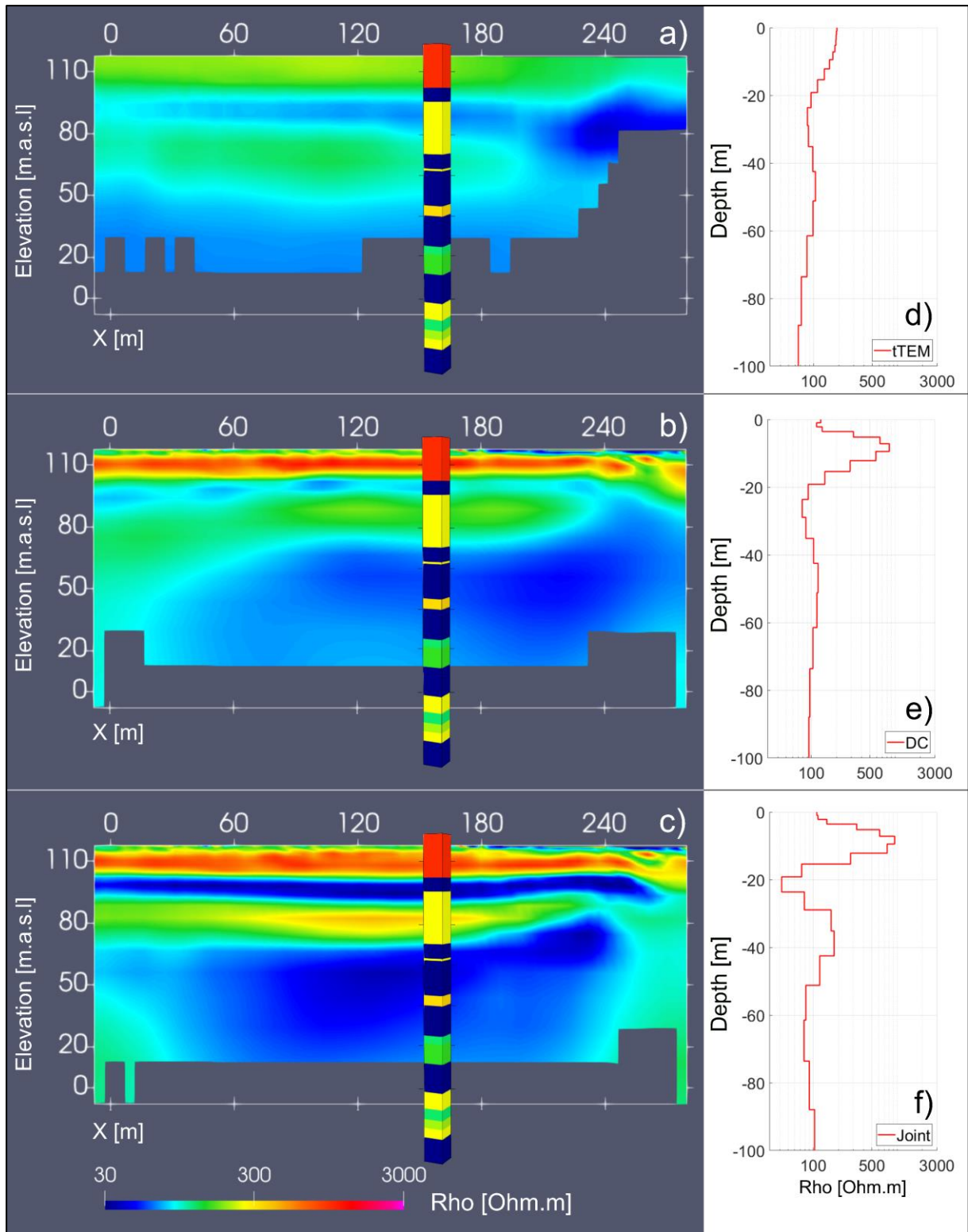


Figure 25: Geophysical models obtained for profile P12 from independent EM (panel a), independent galvanic (panel b), and joint (panel c) inversions. The closest borehole reaching a similar depth is overlaid on the models, where different colours reflect lithological differences. Panels d, e, and f show the 1D models extracted from the 2D models in the left

panels, taken from the closest projection to the borehole location. Note that the vertical scales in the left and right panels are not vertically aligned.

Now that the geophysical models have been validated, we can proceed with some interpretation based on the joint model, as it features the best resolution among the results. Since the joint inversion incorporates induced polarization data from the galvanic measurements, we can also take advantage of the imaginary part of electrical resistivity included in the MPA models to enhance the understanding of subsurface features and improve geological characterization. Figure 26 presents the joint resistivity model in panel a, with the corresponding phase value distribution for the same model shown in panel b from which is evident that a shallow, less chargeable zone is followed at depth by a more chargeable body, before reaching the depth of investigation (DOI). In panel c, contour lines of the phase values at 4, 4.5, and 5.5 mrad are overlaid onto the joint resistivity model. This composition highlights the alignment between the shallow, less chargeable zone and the high-resistivity features, while the deeper, more chargeable zone corresponds to low-resistivity features. From this, we can infer that the shallow, less chargeable zone likely corresponds to the first unsaturated horizon, followed in depth by a clay-rich, chargeable layer, which is also confirmed by the borehole data. Below their DOI, chargeability information becomes unavailable; however, the resistivity anomaly at approximately 80 m.a.s.l. can be interpreted as a potential aquifer horizon. This interpretation is still supported by the borehole, which identifies gravel and pebble deposits at that depth. In panel d, a geological interpretative section derived from the geophysical model is presented from which the following units are derived:

- A shallow zone, between approximately 115 and 100 m.a.s.l., consisting of the surface soil coverage (green unit) and the unsaturated layer below it (red unit).
- A clay-rich layer (blue unit) from 100 to 90 m.a.s.l.
- A potential aquifer-like horizon between 90 and 75 m.a.s.l. (yellow unit), characterized by gravel deposits.
- The deepest clay layer (bottom blue unit) representing the base of the interpretative section, beyond which resolution is limited by the geophysical model.

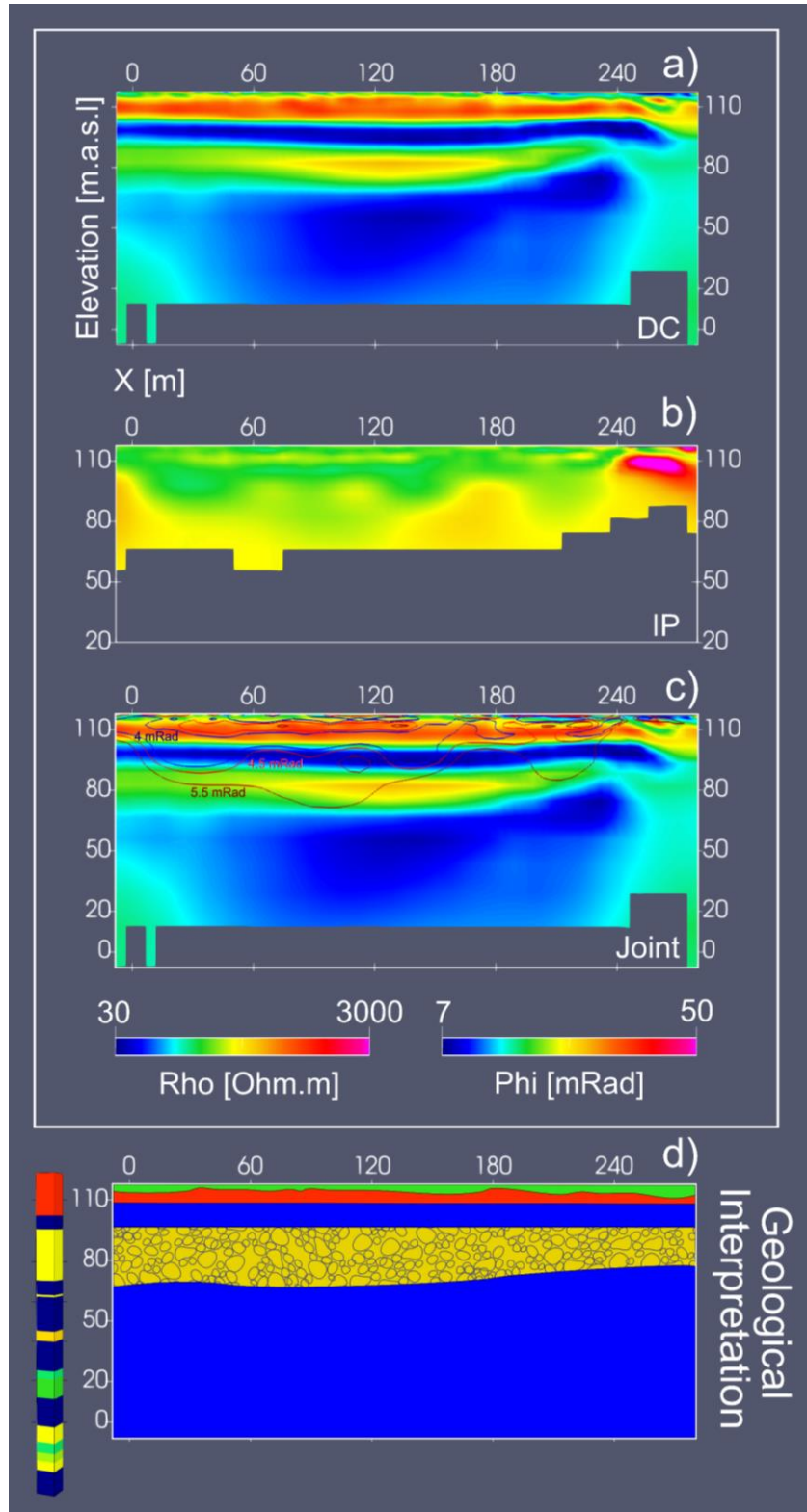


Figure 26: Joint models obtained for profile P_12, showing the resistivity parameter (panel a), the phi parameter (panel b), and an overlay of resistivity with contour lines from the phi model (panel c), with contours at 4, 4.5, and 5.5 mrad. Panel d presents the geological interpretation of the section, including the borehole on the left scaled to the vertical axis.

The primary objective of this geophysical investigation was to achieve the highest possible resolution in describing the subsurface to support the planning of artificial recharge activities at the site. In this context, achieving the highest possible resolution was essential, which likely wouldn't have been possible even if the AEM system had been able to measure in the area, as it would not have provided the required precision to describe the shallow part of the site. This shallow zone is most likely be the portion of the subsurface where the water can be stored. Targeting deeper portions of the subsoil would pose a greater risk to deeper freshwater resources, which must be preserved from potential cross-contamination or migration of agricultural chemicals from nearby cultivated fields. Accordingly, the most probable target identified for water reinjection is the high-resistivity unit between 90 and 75 m.a.s.l., interpreted as a granular horizon likely already hosting a certain amount of water and capable of accommodating additional storage. The joint inversion clearly delineated this geological unit, which is protected by an overlying layer, likely clay-rich, also well defined in the model.

The enhanced resolution of the joint models across the entire survey area (Figure 27) is evident compared to the independent ones. Figure 27 is included, despite the visible model striping (work in progress to eliminate this effect), to highlight these differences and emphasize how the joint models provide valuable information for identifying the optimal location for the infrastructure. Subsequently, by analysing the 1D model at the designated spot, further refinements can be made to forecast the reinjection structure requirements. This approach can help determining the appropriate well depth, the length and placement of screens and filters, and the isolation depth of the borehole bottom, ensuring a well-informed, cost-effective, and environmentally safe reinjection design.

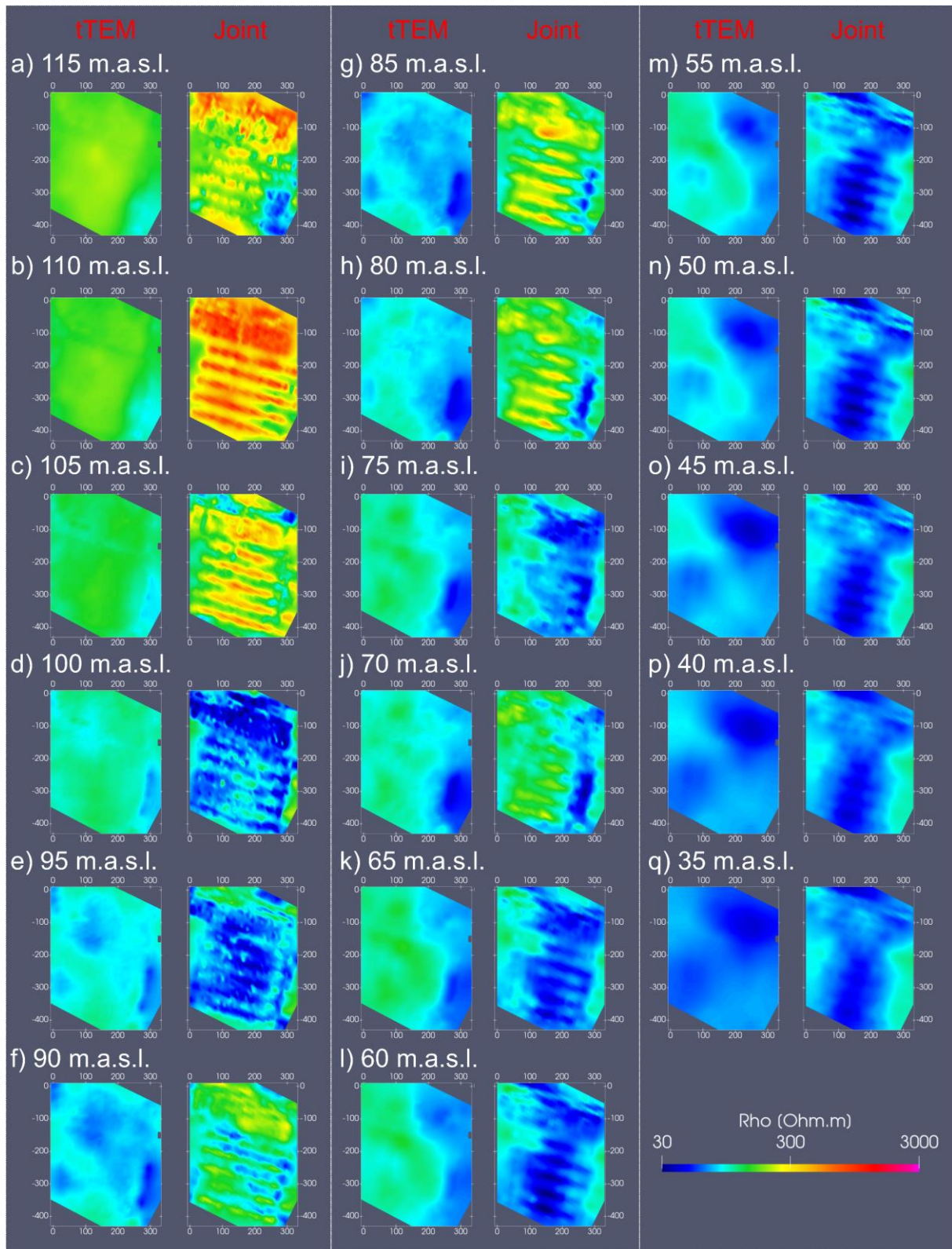


Figure 27: Comparison of depth slices every 5 meters between the independent EM models from tTEM data and the joint models.

2. E&EM TEMPORAL ANALYSIS

To study the evolution of specific physical phenomena or monitor a process, E&EM geophysical techniques can be adapted to capture and describe changes over time. This is usually achieved by collecting multiple datasets at different times and analyzing them through a temporal-analysis approach. This approach begins with purposeful planning of geophysical acquisitions across different time-intervals and, if necessary, spatial locations. The data are then modeled using techniques specifically designed to enhance the detection of target anomalies.

Temporal-studies, therefore, are inherently more sophisticated than traditional E&EM investigations that perform “single-snapshots” of the subsurface which are independently modeled. As said, this added complexity starts at the survey planning stage, where the design must be optimized to capture the specific changes under investigation. Selecting the appropriate geophysical technique and configuring the systems to ensure adequate resolution (e.g., electrode spacing for galvanic monitoring or transmitter and receiver sizes in inductive measurements) is essential. Additionally, it is crucial to account for concurrent physical processes that may occur alongside the evolution of the target anomalies. These parallel phenomena could hinder the desired observations, so the planning may involve solutions (e.g., monitoring) to apply filtering techniques afterwards. The field-approach needs to be complemented by adapting the modeling phase, where all the temporal datasets are integrated within a so-called Time-Lapse modeling framework. This framework aims to enhance the observation of changes that occur against what is considered a relatively stable background. Particularly, the Time-Lapse modeling is meant to emphasize the detection of the target-changes while minimizing model variations that could arise from noise or inversion artifacts. Various Time-Lapse modeling techniques have been proposed in the literature over the years, each with varying characteristics and degrees of complexity (e.g., Daily et al., 1992; Kim, 2005; LaBrecque and Yang, 2001). Applications have also been developed to address temporal investigations across diverse environments and for various purposes. (e.g., Musgrave and Binley, 2011; Johnson et al., 2015; Jodry et al., 2019; Palacios et al., 2020; Paz et al., 2020; Rao et al., 2020; Lapenna and Perrone, 2022; etc.).

In the present work, the term Time-Lapse inversion refers to a modeling approach that integrates all temporal datasets into a single modeling framework. Specifically, the inversions presented next are conducted within a unified framework where all the temporal datasets collectively form the data space.

Another critical aspect for successfully performing Time-Lapse inversion is to properly constrain the temporal models, limiting in the inversion process the non-data-driven variations while preserving the targeted anomalies. To achieve this, the following time lapse modelling adopts the approach proposed by Fiandaca et al., (2015) by employing the Asymmetric Minimum Support Norm (AGMS). The AGSM differ from the classical L2 norm penalizing the number of model components that differ beyond an asymmetric threshold function. The latter allows to control the maximum penalty, the shape of the function, and the threshold value that defines the expected variation of the specific inversion parameter. The characteristics of this norm are further discussed and applied in sections 2.1.2 and 2.1.4 while the shape of the norm function is reported in Figure 28.

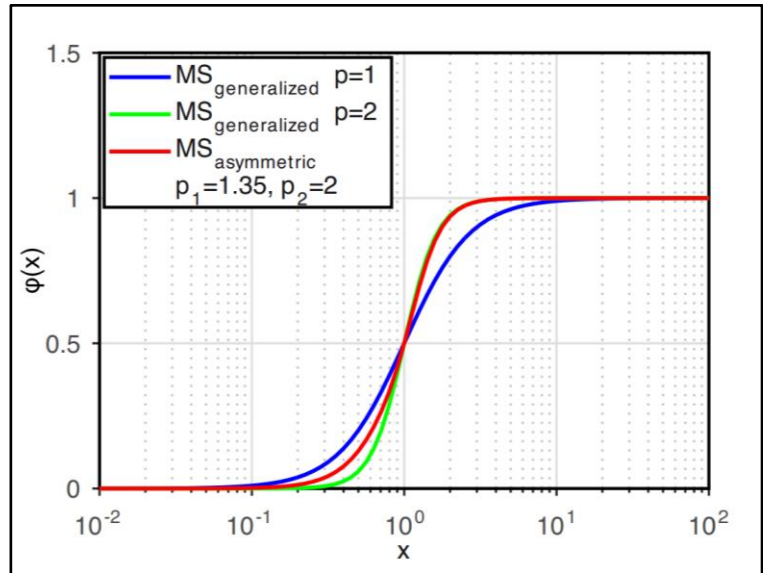


Figure 28: Comparison of the generalized minimum support norm and asymmetric minimum support norms, extracted from Fiandaca et al., (2015)

2.1 TEMPERATURE EFFECT ON E&EM DATA AND MODELLING

Another critical aspect to consider in monitoring studies is that the background model, assumed to be stable outside the anomalies of interest, may not remain constant over time. Other phenomena can also contribute to changes in the subsurface model over time. Whether these changes are secondary or irrelevant to our analysis, they must be treated

as noise. Filtering them out effectively and selectively from the models is especially important when these secondary processes generate anomalies with a greater magnitude than our target anomalies, potentially masking them and preventing their detection.

One of the most significant sources of noise potentially affecting the electrical properties of the subsurface is temperature variation throughout the monitoring period, such as those induced by atmospheric temperature fluctuations. The impact of temperature has already been introduced in Section 1.3.2 and has been extensively recognized in field applications (e.g., Musgrave and Binley, 2011; Gance et al., 2016; Tildy et al., 2017; Blanchy et al., 2020; Lapenna and Perrone, 2022; etc.). Depending on their magnitude and depth of penetration, temperature effects can influence both E&EM measurements when these variations occur within the resolution range of the survey.

In the following sections, an analysis of temperature effects on both galvanic and inductive methods will be presented using both synthetic and real data experiments. In this regard, the first analysis stems from the development of a new methodology designed to address monitoring experiments that do not include direct ground temperature measurements. This methodology is derived from the second Ph.D. paper (Section 2.1.2). Next, in Section 2.1.3, details on how seasonality—and consequently temperature variations—can impact EM system measurements will be explored with a particular focus on their calibration, expanding on the discussion initiated in Section 1.3.

2.1.1 TEMPERATURE EFFECT ON GALVANIC MEASUREMENTS

The effect of temperature on galvanic measurements introduced in the previous sections will be now further discussed. Despite widespread acknowledgment of this effect in the literature, temperature impacts on DC monitoring are often not performed in professional geophysical acquisitions. Instead, temperature data should be collected alongside geophysical data to enable correction and filter out temperature effects. Without this consideration, monitoring experiments risk being compromised if temperature-induced anomalies exceed the magnitude of the target anomalies. The next section reports the second paper produced during the Ph.D. which had a twofold aim: first, to develop an inversion scheme that compensates for temperature effects in DC monitoring lacking direct thermal monitoring, using atmospheric temperature records for the site and incorporating ground thermal diffusivity as an inversion parameter. The second aim of

developing this inversion scheme is to provide a tool that enables investigation of temperature effects on electrical models more broadly. This includes not only models obtained through galvanic systems but also those derived from inductive systems in monitoring experiments or other applications where temperature variation could significantly impact results.

2.1.2 PAPER – MODELLING TEMPERATURE EFFECT IN TIME-LAPSE ELECTRICAL RESISTIVITY TOMOGRAPHY MONITORING THROUGH INVERSION OF THERMAL DIFFUSIVITY

Alessandro Signora¹, Gianluca Fiandaca¹

¹*The EEM Team for Hydro & Exploration, Department of Earth Sciences, University of Milan (Italy). E-mail: alessandro.signora@unimi.it*

*** The manuscript presented in this section is under submission to the Geophysical Journal International and is reported in its complete form. ***

2.1.2.1 SUMMARY

The atmospheric temperature effect on electrical resistivity data is too often overlooked in electrical monitoring surveys and subsequent modelling efforts. This oversight can result in model anomalies orders of magnitude greater than the target anomalies generated by the monitored processes, leading to unusable or misleading results if unaddressed. When not overlooked, temperature correction requires costly and logistically complex ground temperature measurements alongside the resistivity data collection.

In this study, we propose a novel time-lapse inversion scheme, named ARES, to address the impact of atmospheric temperature on subsoil resistivity distribution, eliminating the need for direct subsoil measurements. The ARES correction performs thermal modelling by integrating atmospheric temperature information, such as data from the nearest weather station, to compute the subsoil temperature distribution for all time steps. This is achieved by solving the heat diffusion equation and introducing the thermal diffusivity of the subsoil as inversion parameter. The sensitivity to the thermal diffusivity parameter is achieved by enforcing time-lapse constraints among temporal models. These constraints, within the ARES framework, favour inversion results that minimize

variations caused by temperature effects, achieving the convergence of the time-lapse inversion when the thermal diffusivity parameter value is accurately estimated.

In this work, we first test the effectiveness of the new ARES scheme in correcting temperature effects through comprehensive synthetic testing. Subsequently, the ARES scheme is applied to a 20-month ERT monitoring over a municipal solid waste landfill, where a 3D geoelectrical matrix was installed to monitor waste evolution and locate high-production biogas zones by studying resistivity variation patterns.

The results from this field experiment demonstrate that, without temperature corrections, temperature effects overshadowed the target anomalies, preventing interpretations. With the ARES correction, these temperature effects were effectively filtered out from the inversion models, enabling the detection of anomalies linked to biochemical phenomena and allowing for spatial and volumetric quantitative interpretations.

More broadly, this study aims to present the ARES scheme as innovative technical solution, applicable to a wide range of monitoring studies. It enables the recovery of past geoelectrical monitoring experiments lacking thermal control but affected by strong temperature effects and allow for the design of cost-effective monitoring with simplified logistics, eliminating the need to implement dedicated thermal sensors. Accordingly, practical user guidelines are provided in the work for planning on-site monitoring surveys to be modelled using the ARES scheme.

Key words: *Electrical resistivity tomography (ERT); Time-series analysis; Heat flow.*

2.1.2.2 INTRODUCTION

In recent years Electrical Resistivity Tomography (ERT) has been extensively employed for monitoring natural phenomena evolution performing a series of repeated surveys over time. The effectiveness of monitoring applications has been widely pointed out in literature. For instance, within hydrogeological applications, it has been utilized to image chemical and thermal electrical resistivity (resistivity hereinafter) induced anomalies during tracer experiments (Cassiani et al., 2006; Oldenborger et al., 2007; Doetsch et al., 2012; Hermans et al., 2015), to observe subsoil saturation changes and recharge processes (Binley et al., 2002; French and Binley, 2004; Descloitres et al., 2008), to delineate groundwater watersheds (Miller et al., 2008) and found application also in

geotechnical (Cassiani et al., 2009; Jodry et al., 2019; Boyd et al., 2021) and biological temporal studies (Johnson et al., 2015; Caterina et al., 2017; Rao et al., 2020). The likelihood of detecting a particular phenomenon and its evolution through ERT monitoring depends on the resistivity signature and magnitude associated with the phenomenon, as well as the features of the geophysical survey. In data acquisition, it is crucial to select layouts and settings that are suitable for detecting the target anomalies, taking into account the measurement sensitivities and resolutions. Once the optimal survey options are selected, another important aspect to consider in on-field experiment is the potential occurrence of subsoil variations unrelated to the target processes. These variations must be identified and, if necessary, filtered out using specific data treatment or processing techniques to avoid erroneous interpretations.

In addition to the best practices in field operations, the success of studying temporal evolutions through geophysical surveys depends on the modelling techniques employed. Typically, time-lapse approaches are used to model temporal datasets, which are inherently more sophisticated than the simple differentiation of models derived from separate inversions. The time-lapse techniques aim to highlight target changes while minimizing model variations caused by noise or inversion artifacts and limiting equivalences issues. Various modelling procedures have been proposed in literature to reduce systematic errors consistent over time by applying specific noise cancellation techniques. Examples include ratio inversion (Daily et al., 1992), cascaded inversion (Oldenborger et al., 2007; Miller et al., 2008), and difference inversion (LaBrecque and Yang, 2001). More recently, time-lapse modelling has been advanced by approaches that integrate two or more time steps into a simultaneous inversion, operating within a unified framework where all datasets are included (e.g. Kim et al., 2009; Hayley et al., 2011; Karaoulis et al., 2011a, 2011b). An overview on Time-lapse applications can be found in Singha et al. (2015).

Achieving the highest precision in modelling, thereby retrieving a solution least affected by uniqueness or noise issues, is crucial. This is because model anomalies can also arise from sources unrelated to the target anomaly, often not appearing as easily identifiable outliers but merging with the electrical signature of the target. Numerous phenomena are well-known capable of causing variations in electrical properties during monitoring periods, including hydrological, hydrogeological, anthropogenic, and biological processes.

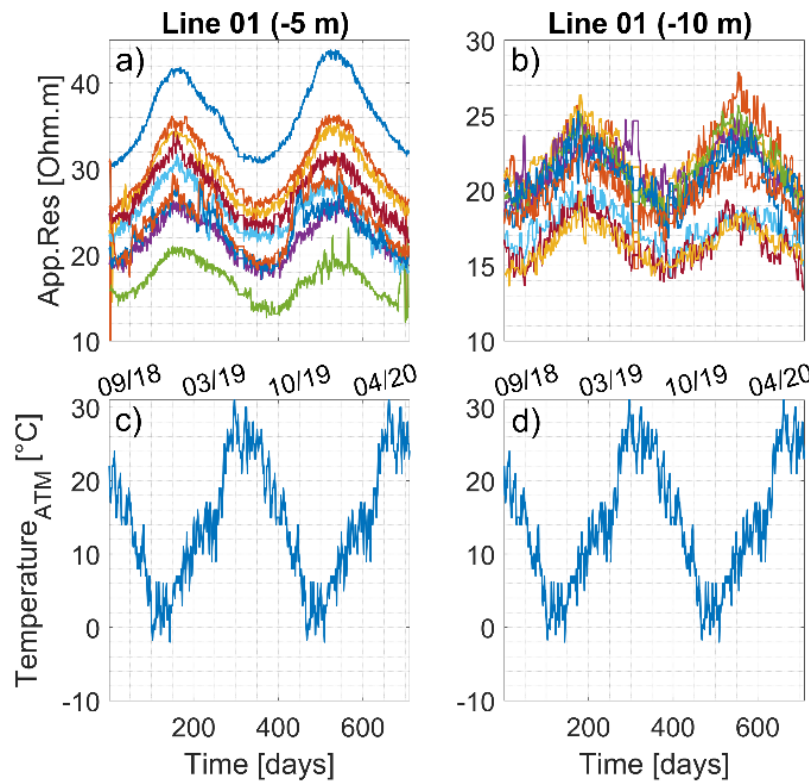
Yet, temperature variations can cause changes in subsoil resistivity of up to 2% per degree Celsius (Hayley et al., 2007), suggesting, for instance, that seasonal atmospheric temperature (T_{ATM}) effects may induce variations potentially greater than those caused by some hydro-chemical phenomena. Temperature variations influence a porous medium electrical response by affecting grain surface resistivity and fluid resistivity. Within the temperature-pressure range relevant to near-surface geophysics, ion conduction is the key factor, governed by the Nernst-Einstein equation below 200°C. Glover (2015) describes how fluid resistivity depends on viscosity, which decreases with temperature, lowering resistivity until a threshold where this effect reverses.

Despite being widely described in the literature and recognized by the geophysical community (e.g., Waxman and Thomas, 1972; Sen and Goode, 1992; Roberts, 2002; Rein et al., 2004; Hayley et al., 2009; Musgrave and Binley, 2011), the temperature effect on electrical monitoring is still often overlooked at the moment of monitoring investigations. When not overlooked, or if temperature variations represent the primary focus for studying the evolving system (e.g., Ramirez et al., 1993; LaBrecque et al., 1996; Musgrave and Binley, 2011; Steelman et al., 2017), these effects must be evaluated in terms of their magnitude on the data, their impact on the final models, and, if necessary, filtered out. In literature various approaches for compensating temperature effects are reported, typically requiring direct measurements of temperature variations in the medium under investigation. These corrections are applied either to the measured apparent resistivity data prior to inversion (Luo et al., 2019; Sherrod et al., 2012) or to the resistivity values in the models after inversion (Brunet et al., 2010; Pellicer et al., 2012; Chambers et al., 2014; Glendinning et al., 2014).

In this work, we aim to propose a time-lapse modelling tool capable of applying temperature-effect corrections directly to resistivity models affected by surface temperature variations (as those induced by atmospheric seasonal oscillations) and not featured by thermal ground measurements at the monitoring time. This effort led to the development of the new ARES (Alpha and RESistivity inversion) inversion protocol, that compensates for temperature effects by incorporating atmospheric temperature data at each time step, solving the heat diffusion equation, and applying a cell-by-cell correction along the model discretization. In this workflow, the thermal diffusivity is estimated during the inversion as a parameter which value is assumed to be uniform throughout the

entire model. Resistivity compensation adjusts the cell resistivity to a reference temperature (e.g., 25°C) following Hayley et al. (2007) approach, which is valid for temperature changes in the range of interest (0–25°C).

In the following, a comprehensive presentation of the ARES inversion scheme is provided, including demonstrations using synthetic models and field validation. The field study includes 20 months of daily ERT acquisitions significantly affected by seasonal temperature variations (Figure 29) and not featured by subsurface temperature measurements. The primary goal of this application was to monitor the evolution of a Municipal Solid Waste Landfill over time, focusing on biogas production and distribution throughout the landfill. Before applying the ARES correction scheme, strong temperature-induced anomalies prevented both quantitative analyses and qualitative interpretations,



hindering any other anomaly-pattern recognition. However, employing the ARES scheme enabled quantitative evolution analysis, with its reliability confirmed through ancillary-data validation. The ARES inversion scheme is developed with a twofold purpose: i) to serve as a recovery tool for ERT monitoring experiments significantly impacted by temperature

Figure 29: Apparent resistivity data acquired during the 20-month monitoring experiment at the different pseudo-depths of -5 meters (A) and -10 meters (B). Each trend curve in the upper plots represents a measuring quadrupole over the monitoring time. The y-axis scale differs for visualization purposes. The temperature variations over the same period are reported in the below graphs (B, C). Refer to APPENDIX A: EFFECT OF ATMOSPHERIC TEMPERATURE ON APPARENT RESISTIVITY DATA or more details on how temperature effects vary with

effects and lacking thermal monitoring data and, ii) to act as a valuable technical solution for planning cost-effective ERT monitoring, removing the need for expensive and logistically challenging thermal measurements.

2.1.2.3 MODELLING APPROACH

UNDERGROUND TEMPERATURE MODELLING

The ARES inversion scheme operates atmospheric temperature correction on the resistivity models removing the T_{ATM} effects from the resistivity variations. This is achieved by inverting for the medium thermal diffusivity (α) in a simultaneous time-lapse inversion, where each model-cell temperature is determined by solving the heat diffusion equation (Eq. (43)) via a finite difference approach:

$$\frac{\partial T}{\partial t} = \alpha \frac{\partial^2 T}{\partial z^2} \quad (43)$$

where the thermal diffusivity value (α) is considered constant for the entire model at all times. As boundary conditions, the temperature at the bottom (T_{BOT}) of the model is considered constant and the T_{ATM} has to be defined for any time and for all depths at the first time step.

Figure 30 presents the solution of the heat equation for all time steps considered in the first synthetic study. It shows the effectiveness of the proposed numerical solution in propagating T_{ATM} effects on resistivity values, reproducing the attenuation and delay of temperature effects with depth, consistently with the behaviour observed on real data (Figure 29, APPENDIX A: EFFECT OF ATMOSPHERIC TEMPERATURE ON APPARENT

RESISTIVITY DATA) and aligning with the analytical solution for the case of a sinusoidal forcing function:

$$T(z, t) = \bar{T}_0 + A_0 e^{-\frac{z}{d}} \sin\left(\omega t - \omega t_0 - \frac{z}{d}\right) \quad (44)$$

Where $T(z, t)$ represent the temperature at the date t [days] and depth z [m] below the surface, $\bar{T}_0$ [°C] is the yearly mean T_{ATM} temperature (at the ground surface) and A_0 [°C] is the yearly amplitude of the T_{ATM} variation. The term $e^{-\frac{z}{d}}$ describes the rate at which the wave amplitude decreases with depth depending on the characteristic penetration depth

$$d = \sqrt{\frac{2\alpha}{\omega}}$$

which define the thermal properties of the subsoil through the thermal diffusivity α . The delay of the subsurface temperature variations increases with depth as well as described by the phase lag $\omega t_0 - \frac{z}{d}$ in the sine term, where $\omega = \frac{2\pi}{365}$ is the angular frequency over the selected period, in this case one year. t_0 represent the origin of the sine function.

In the numerical solution used in our work the sinusoidal forcing function of

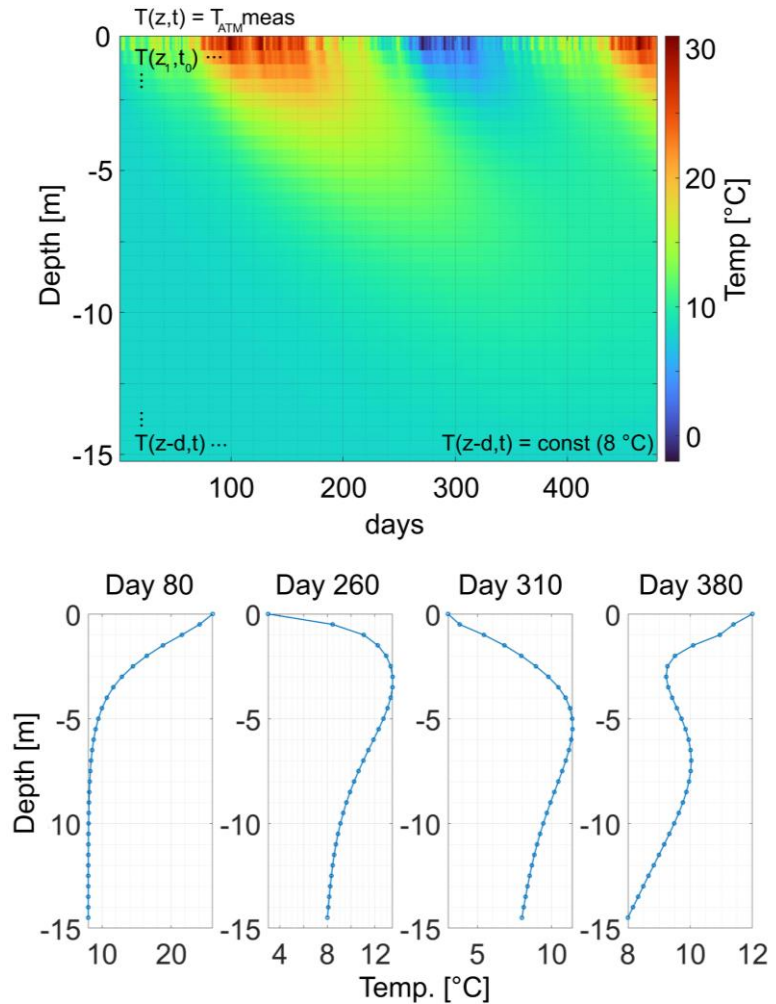


Figure 30: Results of the heat equation solution propagating T_{ATM} effects within the model depth; thermal diffusivity value set to $8.00E-07$ m/s². a) Temperature values along depths and time steps. Boundary condition set for the heat modelling are reported. T_{ATM} data are retrieved from real measurements. b) 1D temperature profiles extracted at different times

Eq. (44) is replaced by the actual T_{ATM} distribution available for the real-case experiment, which is also applied to the synthetic test of section 2.1.2.4. The remaining boundary conditions for temperature modelling in the synthetic tests are explicitly illustrated in Figure 30, along with four 1D models extracted at different time steps, showcasing the variability of the temperature profiles over time. The 1D mesh used for calculating the temperature profile is customizable in terms of maximum depth and vertical discretization. This flexibility allows for the design of a temperature mesh specifically tailored to match the expected temperature model and the characteristics of the geophysical survey. Additionally, it ensures that the temperature effect is propagated only to depths likely to be influenced under the given natural conditions, before reaching the subsoil equilibrium temperature, thereby optimizing computational efficiency.

The numerical solution of the heat equation for modelling the underground propagation of T_{ATM} is performed by solving it in both time and space. Finite differences are used to approximate the second spatial derivative, while the Euler explicit method is applied for the first temporal derivative. This approach incorporates appropriate boundary conditions and assuming the calculation of all temperature values (T) at time t , the finite difference equation becomes:

$$T(z, t + dt) = T(z, t) + CFL \cdot (T(z - dz, t) - 2T(z, t) + T(z + dz, t) + dt) \quad (45)$$

where $T(z, t)$ is the temperature in degree Celsius at the specific z -position and time t ; dz and dt are the spatial and temporal step sizes, respectively. The CFL is the coefficient of Courant-Friedrichs-Lewy coefficient, defined as:

$$CFL = \alpha \cdot \frac{dt}{dz^2} \quad (46)$$

Where α is the thermal diffusivity of the medium.

To ensure numerical stability when solving the heat equation and to guarantee convergence of the partial derivatives, the CFL coefficient must remain below 0.5. However, during the practical inversion processes with the ARES protocol, adjustments of the thermal diffusivity parameter (α) are expected through the iterations, as detailed in the next section. These adjustments may lead to an increase in the CFL value above 0.5, potentially destabilizing the solution. To address this issue when dealing with higher α values, the time interval between temperature steps is reduced through spline

interpolation, ultimately lowering the CFL value. Since the ARES scheme requires solving the heat equation for all time steps between t_0 and t_{END} (where t_{END} represents the time step corresponding to the time-lapse resistivity model), the inversion iteration-time is highly dependent on the number of steps used to compute the numerical solution of the heat equation. Consequently, stabilizing the solution increasing the step number results in increased iteration times within the ARES inversion. This effect is shown in APPENDIX B: NUMERICAL STABILITY OF THE THERMAL MODELLING WITH IMPLICATIONS FOR ARES INVERSION SCHEME.

ARES TIME-LAPSE INVERSION SCHEME

The ARES correction is featured by a time-lapse architecture that plays a central role in achieving the temperature correction. In fact, during the iterative process, the sensitivity to thermal diffusivity parameter is brought by enforcing time-lapse constraints between temporal models. These constraints favour models where the temperature effect is effectively compensated, thus model variations reduced. Within the ARES inversion, this condition is achieved when the iterative process converges to a correct and representative estimation of the thermal diffusivity parameter, through which the thermal model is calculated (Eq. (43)). In fact, the minimization of the objective function (Eq. (47)) is governed by the total misfit which includes the time-lapse constraints term. Convergence is achieved when an accurate value for the subsoil thermal diffusivity is retrieved, leading to a reduction in the time-lapse constraint misfit.

More specifically on the time-lapse constraints, this work builds on the developments presented by Fiandaca et al. (2015), which allows more control and the inversion process via the asymmetric minimum support norm. This method has been shown to favour compact variations in the model parameter distribution (Last and Kubik, 1983; Portniaguine and Zhdanov, 1999). The time-lapse approach in this work integrates all temporal datasets into a unique simultaneous inversion where each temporal model is constrained against the preceding one. Consequently, the objective function (φ) becomes:

$$\varphi = \varphi_d(\delta d) + \varphi_{TL}(\delta m) + \varphi_R(\delta r) \quad (47)$$

where φ_d , φ_{TL} , φ_R , represent the misfit measures for data, time-Lapse constraints, and roughness constraints, respectively.

In the time-lapse approach φ_{TL} and φ_R split the regularization in two terms, highlighting further complexity compared to the independent inversion. Specifically, the intra-model constraints (φ_R), set internally to the models, favour smooth solutions, while the time-lapse constraints (φ_{TL}) limit the differences between consecutive temporal models, promoting the recovery of compact changes. The time-lapse inversion proposed in this work follows an iterative process, consistent with the commonly used approach of linearizing the nonlinear forward mapping from the model to the data space, as illustrated by the equation below:

$$m_{(n+1)} = m_{(n)} + [G_{(n)}^T C_{d(n)}^{-1} G_{(n)} + \lambda_{(n)} I]^{-1} \cdot [G_{(n)}^T C_{d(n)}^{-1} \delta d_{(n)}] + \quad (48)$$

where the parameter $\lambda_{(n)}$ represents the iteratively updated damping factor (Auken et al., 2014a), $G_{(n)}^T$ denotes the Jacobian, $\delta d_{(n)}$ represent the update to the data vector, and $C_{d(n)}^{-1}$ stands for the inverse of the covariance matrix.

In this study the time-lapse inversion approach differs from that of Fiandaca et al. (2015), since the model vector includes the resistivity at the reference temperature of 25 °C and the thermal diffusivity value (α), assumed as a single value representative of all models. After solving the heat equation (Eq. (43)) for all layers and time-steps, the new ARES model vector is defined. For each cell in the model discretization, it defines: i) the resistivity of the cell at the reference temperature and ii) the cell temperature as a function of T_{ATM} , with the lower boundary condition set to a constant temperature at the model's base. The forward response is calculated by incorporating the cell resistivity adjusted to the reference temperature, using the equation proposed by Hayley et al. (2007):

$$\sigma_T = (1 + m(T - T_{25}))\sigma_{25} \quad (49)$$

where σ_T represents the electrical conductivity (inverse of electrical resistivity) of the medium the temperature a T , σ_{25} is the electrical conductivity of the medium at the reference temperature of 25 degree Celsius (T_{25}), and m represents the fractional change in electrical conductivity per degree Celsius. In this work, the value of m is set to 1.83%, consistently with the value found Hayley et al. (2007) for temperatures ranging between 0 and 25 °C.

The forward mapping is then performed by solving the differential equation on the forward mesh, the misfit is calculated, and the model is finally updated as outlined in Eq.

(48). As the ARES inversion progresses through iterations and the thermal diffusivity parameter is gradually updated, the misfit decreases as the α estimation approaches the real value, leading to more compact solutions through more effective temperature compensation.

2.1.2.4 SYNTHETIC RESULTS

Two synthetic simulations are presented in the following sections to evaluate the ARES inversion scheme accuracy in performing the temperature correction. The first test demonstrates its effectiveness in correcting the T_{ATM} effect in the time-lapse models. The second explores the practical boundaries of the ARES scheme, providing guidance for scheduling monitoring survey in contexts where temperature-induced effects on electrical resistivity are significant, and no thermal monitoring is planned.

FIRST SYNTHETIC STUDY: ARES SCHEME ASSESSMENT

In the first synthetic experiment, we simulate the spreading of a low resistivity plume, featured by values ranging between 120 and 140 $\Omega \cdot m$ at 25 °C, over a homogeneous background half-space at 150 $\Omega \cdot m$. The spreading is simulated to occur over six months, with time steps set at distances of 30 days apart mimicking the transition from winter to summer temperature conditions. This is achieved using a temperature model generated from real T_{ATM} data (Figure 29c). Seven synthetic datasets were generated for this experiment by computing the forward responses from the initial models shown in Figure 31, column a, and perturbing each with different temperature models. Those were generated by setting a homogeneous thermal diffusivity value of 8.00E-07 m²/s, representative of non-consolidated sediments (Dalla Santa et al., 2020), and a unique bottom temperature of 8 °C at a depth of -15 meters from the surface. The galvanic sequence used in this test consists of a multiple gradient array (Dahlin and Zhou, 2004) with 81 electrodes spaced 5 meters apart, resulting in over 1440 measuring quadrupoles. At each time step, uncorrelated Gaussian noise with a standard deviation of 1% is added. The datasets generated have been first inverted employing the time-lapse constraints without temperature modelling (Figure 31, column b). Then the same datasets have been inverted with the ARES scheme to compensate for the T_{ATM} effect (Figure 31, column c). In Figure 31, the non-corrected and the corrected models are reported for just three time

steps to maintain brevity, ensuring to display the models at the different seasons. The first model of each column represents the baseline in terms of resistivity distribution, while the others are shown as model ratios calculated by dividing cell-by-cell the resistivity values of the baseline by those of the $-ith$ model. Therefore, an increase in the $-ith$ cell resistivity value results in a ratio below one, represented as a blue anomaly in the sections. Conversely, red anomalies indicate a decrease in the resistivity of the $-ith$ model. In Figure 31, column b, data misfit sections for the 0^{th} , 3^{rd} , and 6^{th} models without temperature correction show average χ values of 1.02, 1.04, and 1.20. For the same models now obtained using the ARES inversion (column c), the misfit are 1.01, 1.00, and 1.07 respectively, indicating a slight misfit improvement.

The comparison between the non-corrected models and the true ones reveals the inaccuracy of the models lacking temperature correction in retrieving accurate resistivity distributions. Specifically, a resistivity band anomaly is observed down to a depth of -15 meters, corresponding to the zone where T_{ATM} effect is expected to be significant. In contrast, the ARES models more accurately resemble the resistivity of the true models. More in detail, the third non-corrected ratio model (Figure 31, column b, `RATIO_03`) exhibits a flat and continuous red anomaly in the shallow part. This indicates a decrease in resistivity caused by the increased T_{ATM} effect on the subsoil model, as appreciable in Figure 30 (`RES_0`: Day 300, `RATIO_3`: Day 390), consequently hindering the plume extent. Consistently, the sixth non-corrected ratio model (`RATIO_06`) reveals an even more pronounced low-resistivity anomaly, resulting from the transition to full summer season temperatures (`RATIO_06`: Day 480 in Figure 30). Conversely, the corresponding ARES models (Figure 31, column c, `RATIO_03`, `RATIO_06`) effectively compensate for the T_{ATM} effect, eliminating the low-resistivity shallow anomaly and recovering the plume extent. In terms of thermal diffusivity value estimation, the ARES protocol retrieved an inverted alpha value (α_{inv}) of $1.07E-06 \text{ m}^2/\text{s}$, indicating a deviation of approximately 25% from the true alpha value (α_{TRUE}) of $8.00E-07 \text{ m}^2/\text{s}$ used for generating the forward responses. Despite this discrepancy, the ARES correction demonstrates a satisfactory improvement of the models, filtering the T_{ATM} that affected the non-corrected models.

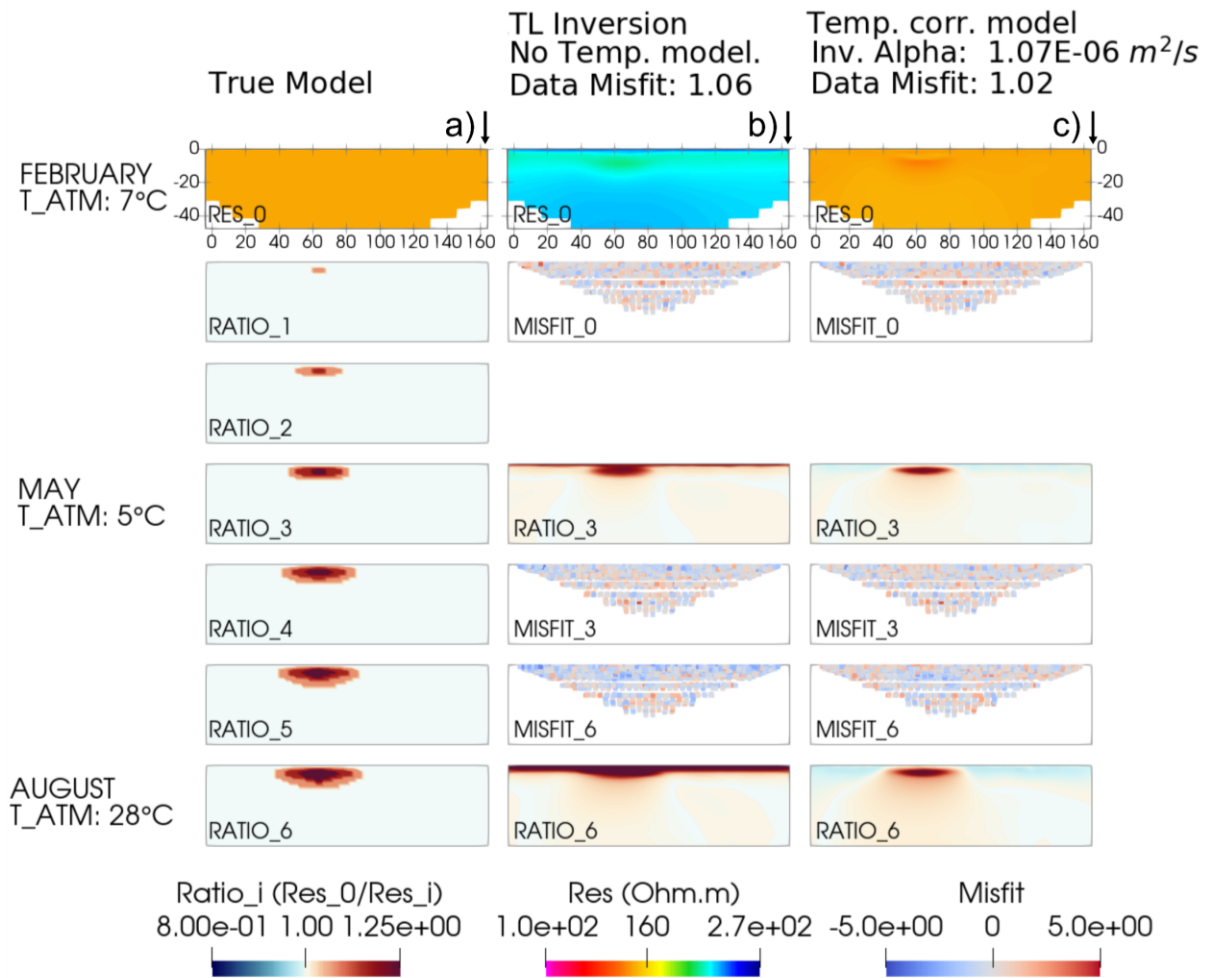


Figure 31: First synthetic experiment: a) True models used to generate the forward responses and simulating the spread of a conductive plume (120-140 $\Omega \cdot \text{m}$) over a period of six months. The background half-space is set to 150 $\Omega \cdot \text{m}$. b) Inversion results (RES_0, RATIO_ith) and respective misfit sections (MISFIT_ith) obtained without the temperature correction. c) Inversion results (RES_0, RATIO_ith) and misfit (MISFIT_ith) sections obtained through the ARES scheme. The ratios in each column are computed by dividing the first model (RES_0) by the subsequent in time (ith).

SECOND SYNTHETIC STUDY: GUIDELINES FOR SURVEY DESIGN

The second synthetic experiment aims to explore the applicability boundaries of the ARES inversion scheme. Its primary objective is to better understand the accuracy needed in retrieving the thermal diffusivity inversion parameter (α_{inv}) to accomplish accurate temperature corrections. This analysis evaluates the results of numerous synthetic tests in retrieving α_{inv} , each of them perturbed with different temperature models that simulate various seasonal conditions during the monitoring. The second goal is to establish

practical guidelines for scheduling monitoring surveys in contexts where temperature-induced effects on electrical resistivity are expected to be significant, yet no thermal monitoring is planned.

The synthetics forward generation starts with the same seven true-models as of Figure 31, column a. For the temperature perturbations in the forward response calculations, the same boundary conditions of the previous test apply (thermal diffusivity: $8.00\text{E-}07 \text{ m}^2/\text{s}$, bottom temperature: $8 \text{ }^\circ\text{C}$, equal T_{ATM} distribution). The test assesses the ARES protocol by progressively advancing the starting time by one month, from January to December, for a total of twelve time-lapse inversions, during which the true models remain constant while the forward generations are perturbed by varying T_{ATM} values.

This approach first aims to determine what constitutes an effective inversion estimation of the alpha value (α_{inv}) testing different temperature patterns. To further stress the ARES protocol evaluation, the same analysis is performed reducing the time steps number to four (3-month survey) to minimize the ΔT_{ATM} and push the sensitivity on the model parameter α_{inv} to its lower limit (see Section 2.1.2.3).

Figure 32 graphically presents the results of these tests, which are extensively reported in Table 9. The first column of Table 9 lists all the α_{inv} values obtained from the twelve experiments with shifted starting months. In all cases, the ARES temperature correction proved effective, indicating that the retrieved α_{inv} range (from $7.13\text{e-}07$ to $1.07\text{e-}06 \text{ m}^2/\text{s}$) is sufficiently accurate.

Figure 32a and b show the test results for the cases in which the maximum (Figure 32a; Table 9, first column - July starting step period) and minimum (Figure 32b; Table 9, first column - February starting step period) values of α_{inv} have been retrieved. For brevity, only four of the seven models are displayed.

Figure 32a' and b' reports the corresponding uncorrected models, emphasizing the strong influence of T_{ATM} on the models. Specifically, in Figure 32a' the T_{ATM} effect prevents the delineation of the plume extent due to the superimposition of the low-resistivity anomaly induced by summer temperatures with the similarly low-resistivity plume anomaly. In Figure 32b' the delineation of the plume extent appears feasible, as the strong winter T_{ATM} effect induces a high-resistivity anomaly that now contrasts with the plume signature. However, the T_{ATM} effect dominating the shallow part of the model may

hinder other significant high-resistivity anomalies. Therefore, the elimination of this effect is still considered necessary.

The second column of Table 9 reports all the α_{inv} value retrieved by replicating the previous experiments reducing now the time step to four. Even in these reduced-step test, whose models are not shown for brevity, the correction T_{ATM} effect is consistently achieved.

For completeness, Figure 32c shows, for each test, the maximum delta temperature observed during the period of interest. The orange solid and dotted lines represent the maximum delta temperature for the 3- and 6-months experiments, respectively. All the delta temperature values are also listed in Table 9.

Building on this, Figure 32d presents the analysis on how the retrieved thermal diffusivity value impacts the modelling, which results are reported also in the third column of Table 9. This figure aims to quantify how variations in α affect the forward responses, helping to understand the impact that the accuracy of this parameter estimation has on the modelling results. Alpha test values (α_{TEST}) are first varied from the minimum and maximum values identified in the previous test (Figure 32d, edges of the red band) and then increased and decreased by up to 100 times α true value.

Table 9: The first and second columns report the α_{inv} values retrieved in the twelve-month experiments respectively featured by 7 and 4 time steps. The maximum delta temperature for each inversion test is reported within round brackets. The third column details the α_{TEST} values and the respective misfit obtained in the thermal diffusivity test. The endmember α values identified in the first test and used in the second are highlighted with red font. The blue-filled cell indicates the test where α_{TEST} is set equal to α_{TRUE} , with the corresponding value reported in the green-filled cell.

	① 12-month test (4 time steps)	② 12-month test (7 time steps)	③ T. diff. test	
Start month	α_{inv} [m ² /s]	α_{inv} [m ² /s]	α_{TEST} [m ² /s]	Data misfit
JAN	8.67E-07 (ΔT_{ATM_MAX} : 11 °C)	9.61E-07 (ΔT_{ATM_MAX} : 25 °C)		
FEB	1.05E-06 (ΔT_{ATM_MAX} : 9 °C)	1.07E-06 (ΔT_{ATM_MAX} : 21 °C)	8.00E-09	3.17
MAR	9.45E-07 (ΔT_{ATM_MAX} : 19 °C)	9.92E-07 (ΔT_{ATM_MAX} : 21 °C)	8.00E-08	2.71
APR	1.00E-06 (ΔT_{ATM_MAX} : 15 °C)	9.34E-07 (ΔT_{ATM_MAX} : 17 °C)	4.00E-07	1.16
MAY	9.39E-07 (ΔT_{ATM_MAX} : 12 °C)	8.46E-07 (ΔT_{ATM_MAX} : 28 °C)	7.13E-07	0.2
JUN	8.97E-07 (ΔT_{ATM_MAX} : 9 °C)	8.03E-07 (ΔT_{ATM_MAX} : 22 °C)	8.00E-07	0.00
JUL	8.11E-07 (ΔT_{ATM_MAX} : 13 °C)	7.13E-07 (ΔT_{ATM_MAX} : 27 °C)	1.07E-06	0.51
AUG	7.69E-07 (ΔT_{ATM_MAX} : 19 °C)	7.33E-07 (ΔT_{ATM_MAX} : 27 °C)	1.60E-06	1.19
SEP	7.78E-07 (ΔT_{ATM_MAX} : 12 °C)	7.46E-07 (ΔT_{ATM_MAX} : 18 °C)	8.00E-06	3.94
OCT	7.32E-07 (ΔT_{ATM_MAX} : 14 °C)	8.08E-07 (ΔT_{ATM_MAX} : 14 °C)	8.00E-05	8.95
NOV	7.67E-07 (ΔT_{ATM_MAX} : 8 °C)	9.04E-07 (ΔT_{ATM_MAX} : 24 °C)	α_{TRUE} : 8.00E-07 [m ² /s]	
DEC	7.81E-07 (ΔT_{ATM_MAX} : 9 °C)	8.77E-07 (ΔT_{ATM_MAX} : 24 °C)		

The analysis of Figure 32d and Table 9 shows that as α_{TEST} decreases, the misfit value progressively increases, reaching 3.17 points when α_{TEST} is reduced to one-hundredth of α_{TRUE} . This simulates a lower-limit condition with limited temperature effects. Consistently, as α_{TEST} increases, the misfit value follows a steeper trend, reaching 8.95 points when α_{TEST} increases to one hundred times the true value. Under this condition, the magnitude of the T_{ATM} effect is significantly amplified reaching deeper layers of the model.

14 The misfit values obtained for the extreme α_{TEST} highlight the significant impact of this
15 parameter variations on the ARES forward response, especially considering the large
16 scale of the 1440-quadrupole galvanic sequence employed. In this context, the α_{INV} value
17 interval retrieved from the 12-month tests is reinforced as representing an acceptable
18 accuracy range. This is supported also by the fact that all the inversions retrieving both
19 the extreme and intermediate α_{INV} values effectively performed the temperature
20 correction, also yielding inversion misfits below the galvanic noise level added to the
21 synthetic data (1% Noise STD).

22 In terms of user guidelines for scheduling ERT monitoring surveys to be corrected
23 afterward using the ARES protocol, the 4 time-step tests demonstrate to consistently
24 correct temperature effects leading to a good data fit. This suggests that conducting four
25 surveys over a three-month period, for instance, would be sufficient to obtain an accurate
26 α_{INV} value with the ARES inversion.

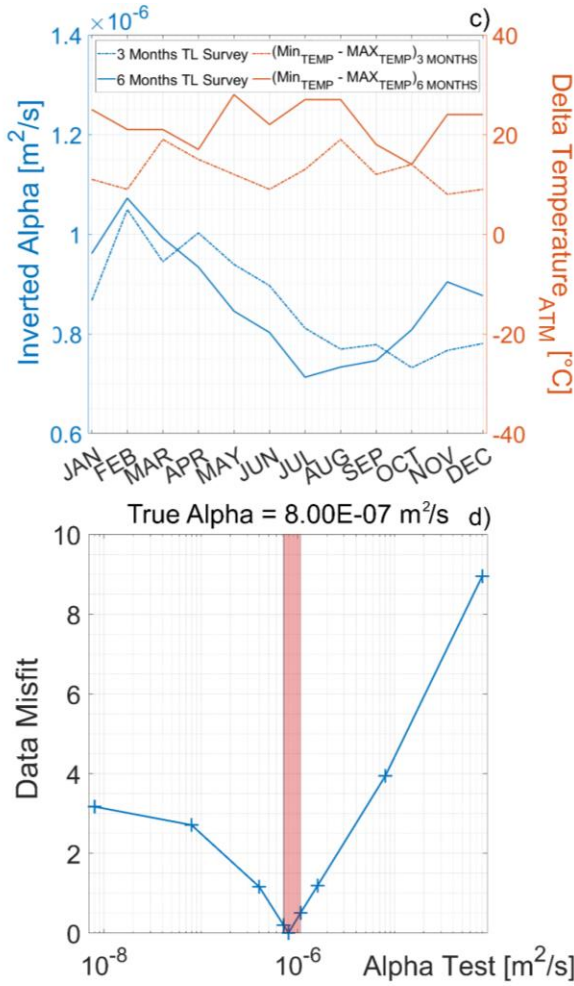
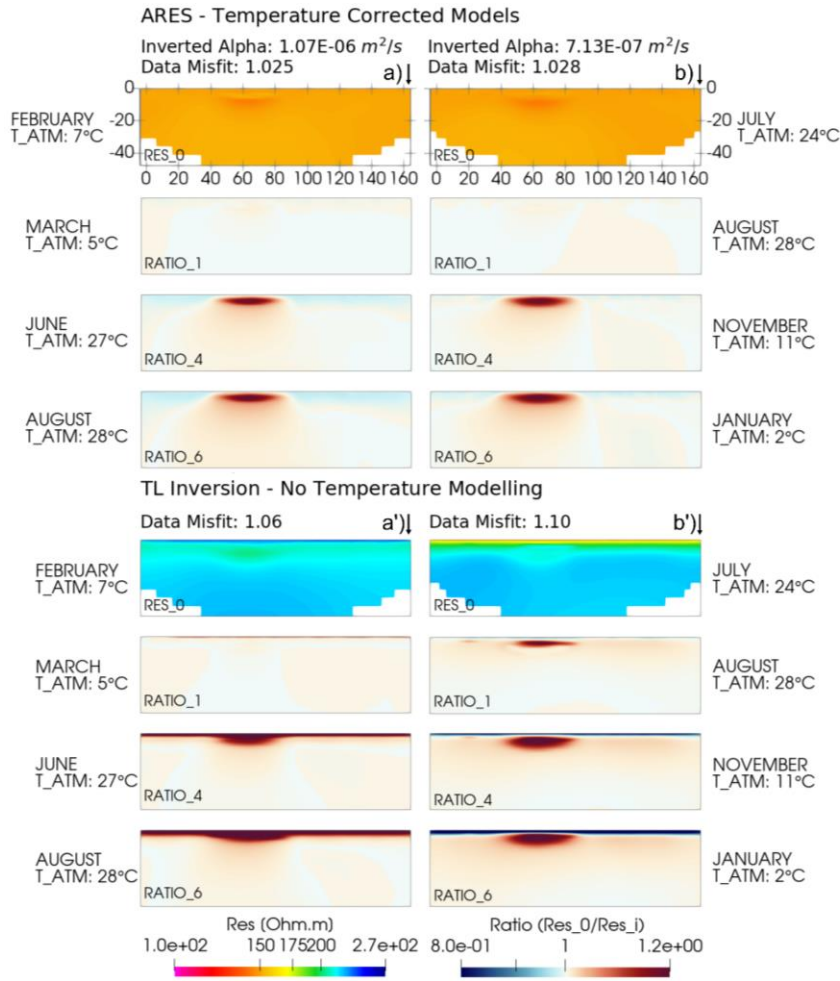


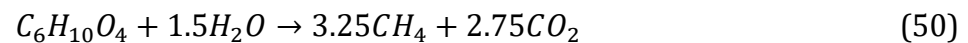
Figure 32: Second synthetic experiment: a) Resistivity models from the ARES inversion with the highest α_{INV} value retrieved among the twelve tests. a') Corresponding models without temperature correction. b) Resistivity models from the ARES inversion with the lowest α_{INV} retrieved value b') Corresponding models without temperature correction. c) α_{INV} values retrieved for the 4 time-steps (blue dotted line) and 7 time steps (blue line) experiments. Orange lines represent the maximum ΔT_{ATM} ($^\circ\text{C}$) of the 4 time steps (orange dotted line) and 7 time steps (orange line) tests. d) Misfit analysis comparing the forward responses using an α_{TEST} value different from α_{TRUE} .

2.1.2.5 FIELD CASE STUDY

LANDFILL BIOGAS MONITORING

In this section, the ARES inversion scheme is applied to a real case study involving a 20-month monitoring ERT survey conducted over the rooftop of a Municipal Solid Waste (MSW) landfill (Figure 33). The survey consisted of two automated daily measurements, conducted in the morning and evening via a remotely controlled geoelectrical system. Stainless-steel electrodes were installed in chambers approximately 30 cm deep (Figure 33c) within the waste and beneath the waterproof cover designed to prevent rain infiltration and create a close system. The primary objective of the monitoring was to identify concentration areas of biogas production, which is extracted through pumping wells for thermo-energy production purposes. Typically, these pumping wells are installed within the waste body following regular grids, the shape of the landfill structure, or based of ancillary information on waste distribution. However, this practice often leads to the drilling of non-productive wells in sterile areas or wells with low biogas production performance, resulting in shortened well-lifespan and inefficiencies in the extraction process.

In an MSW landfill during its third anaerobic degradation stage, as is the case with our landfill, methane becomes the primary chemical component of the biogas (Christensen et al., 1994; Themelis and Ulloa, 2007). Methane production results from the biodegradation of organic waste, driven by microorganisms through reactions such as the methanogenic process (Eq. (50)). This bioreaction primarily produces methane, followed by carbon dioxide, water, and other minor components in an exothermic process that, for a generic organic compound, can be formulated as:



In literature, previous geophysical studies (Moreira et al., 2014, 2015; Mendonça et al., 2015; De Vasconcelos et al., 2023) suggest that productive biogas zones can exhibit diverse electrical signatures. Therefore, defining these zones solely based on resistivity

contrasts could be ambiguous. In this work, we aim to locate the high-production biogas zones within the landfill by studying seasonal resistivity variation patterns.

The most productive biogas areas are in fact expected to correspond to the most electrically-dynamic portions of the waste, providing a way for unequivocal identification based on temporal resistivity variations. Since the methanogenic process is driven by bacterial activity, it follows a seasonal pattern linked to bacterial physiology. In MSW landfills, peak bacterial activity and biogas production typically occur during the warmer summer months. Consequently, these months will be the focus for pinpoint the most and least methane-productive areas.

To address these investigative purposes, the ARES inversion reveals necessary as the 20-month data show strong temperature effects (Figure 29, APPENDIX A: EFFECT OF ATMOSPHERIC TEMPERATURE ON APPARENT RESISTIVITY DATA). In the next section, a detailed description of the data acquisition setup and the characteristics of the modelling approach will be provided. Then, modelling results will be presented and ultimately validated through comparison with ancillary information.

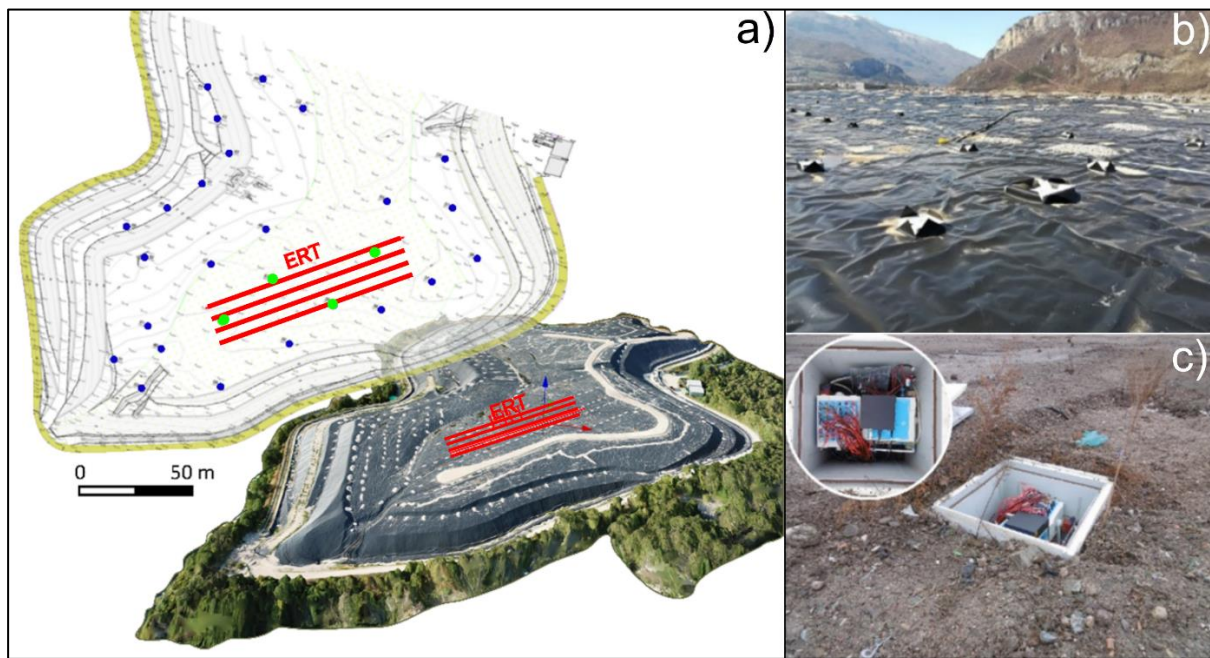


Figure 33: Municipal landfill where the 20-month ERT monitoring has been performed. a) Planimetric and three-dimensional views of the landfill. Red lines depict the ERT profiles, while the blue and green dots indicate biogas pumping wells outside and within the survey area, respectively. b) View from the landfill rooftop showing the locations of electrode chambers. The black waterproof cover protecting the landfill from water infiltration is also

visible c) Electrode chamber embedded in the landfill body with a close-up of the chamber hosting the georesistivity-meter.

ERT ACQUISITION AND DATA TREATMENT

The ERT monitoring survey featured twice-daily acquisitions along four parallel profiles positioned on the landfill rooftop (Figure 33b). Electrodes were placed within the body waste and remained in position throughout the whole study, housed within concrete chambers (Figure 33c) that allowed for access if maintenance was required. Each of the four lines consisted of 18 stainless-steel electrodes spaced 5 meters apart (Figure 33a), with the lines themselves positioned 5 meters apart to create a pseudo-3D acquisition matrix. A modified version of the Electra Matrix (Moho S.r.l.) system was utilized for performing the resistivity measurements, featuring multi-channel acquisition with a peak-to-peak AC current injection of ± 200 mA, adjustable measurements up to 400 V, and a sampling frequency of 512 Hz, benefited by A/D converters placed at the cable takeouts to ensure signal preservation during transmission.

The monitoring period spanned from January 2019 to August 2020, during which the waste structure remained stable, and the waterproof cover had been in place for several months since its construction, preventing rainfall infiltration and creating a closed system within the waste. The analysis aims to study variations on monthly basis, pointing to discern a seasonal evolution pattern. For this purpose, data from the first ten days of each month are extracted to derive the final dataset. Within these ten days, only afternoon measurements are selected and averaged to enhance the signal-to-noise ratio, with the standard deviation subsequently recalculated. The recalculated standard deviation for each new measurement is then incorporated into the inversion objective function (Eq. (47)). Therefore, the final dataset for the 20-month period comprises four ERT surveys per month, resulting in a total of 80 datasets. These have been processed using the EEMStudio software (Sullivan et al., 2024), to ensure accurate outlier culling across all datasets.

INVERSION FEATURES AND MODELS

The modelling approach for the real-case data employs the ARES inversion scheme, that expects the thermal diffusivity (α) of the subsoil as inversion parameter as presented in the previous sections. The objective is to compensate for the significant atmosphere

temperature effects (T_{ATM}) observed in the data acquired during the 20-month monitoring period (Figure 29, APPENDIX A: EFFECT OF ATMOSPHERIC TEMPERATURE ON APPARENT RESISTIVITY DATA). Differently from the synthetic test previously presented, the bottom temperature is now set to 50 °C in accordance with ancillary information provided by the landfill managers, as is common for such non-geological environment (e.g., Bingemer and Crutzen, 1987). The T_{ATM} time sequence measurements are obtained from the nearest weather station to the field site.

The 80 datasets have been simultaneously inverted in a single time-lapse inversion process, with Time-lapse constraints applied between models at each time-step and between spatially adjacent models. Thereby, this approach incorporates both temporal and spatial regularization, in addition to the internal regularization applied to each model. This inversion process produced twenty 3D models, depicting variations occurring over time and space within the waste body.

In Figure 34 the landfill modelling results are presented for both the classical time-lapse (Figure 34, column b) and for the ARES correction modelling (Figure 34, column c), allowing for comparison between the two approaches. Figure 34, column a, displays the recalculated data standard deviation, with each quadrupole-STD value shown in its respective position in the data pseudo-section. For brevity, three time steps out of the total 20 are selected, chosen to highlight the seasonal T_{ATM} variation effect on the resistivity models.

The first model in Figure 34, columns b and c, represents the baseline model in terms of resistivity values. These models are clipped over the Depth Of Investigation (DOI), as defined in Fiandaca et al., 2015. The two models below in each column ($RATIO_{ith}$) display the ratio between the initial model (RES_0) and the i -th models. In this representation, a decrease in resistivity in the i -th model appears as values greater than one (blue anomalies), while an increase is shown as values lower than one (red anomalies). In the non-corrected model ratios, a clear low resistivity anomaly caused by warmer temperatures is evident (Figure 34, Column b, MAY_20 and AUG_20 - blue band anomaly), preventing any other anomalies detection. Conversely, the corresponding ARES temperature corrected models exhibit significant improvements, enabling the recognition of independent anomalies evolving over time, characterized by both decreased and increased resistivity. Notably, the ARES inversion achieves a slightly improved misfit

compared to the classic time-lapse inversion (see Figure 34 column headers). These results indicate that the ARES scheme successfully compensated for the T_{ATM} effect in the models, yielding an estimated α_{inv} value of $3.53E-06 \text{ m}^2/\text{s}$.

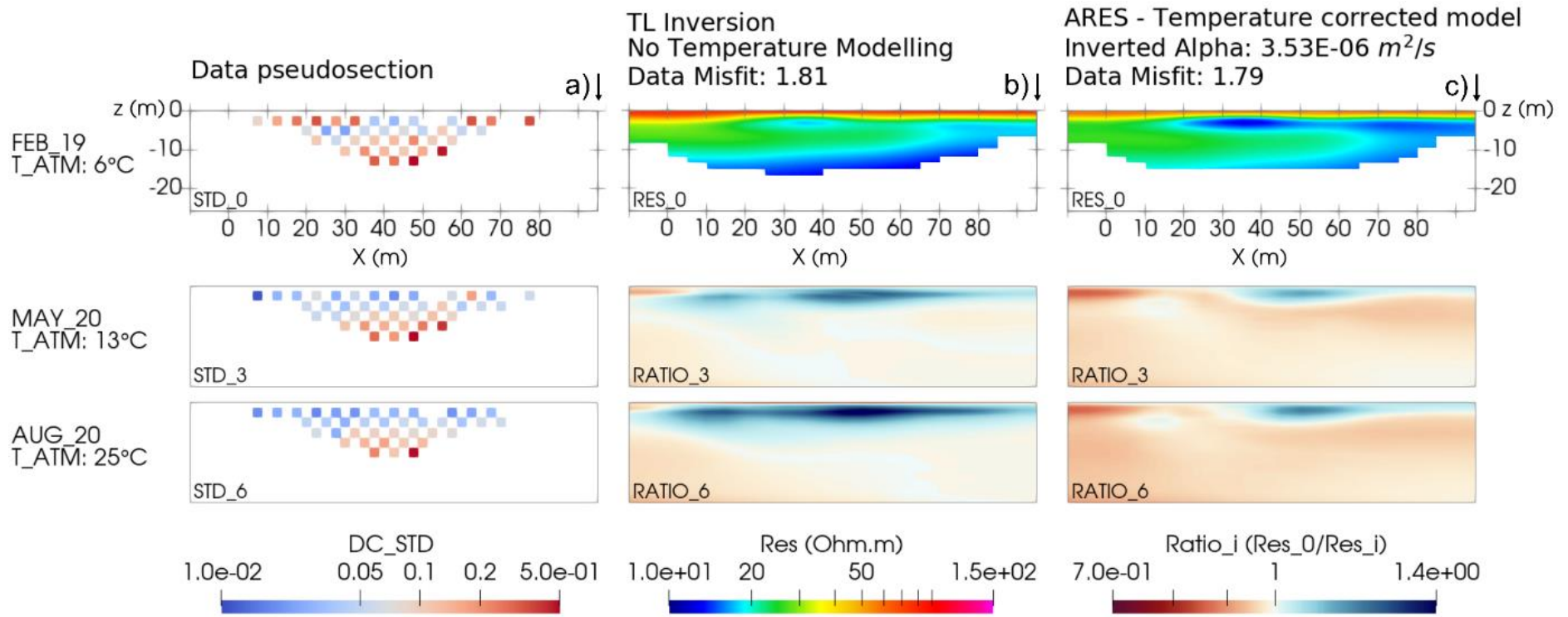


Figure 34: Inversion results of the 20-month monitoring experiment over the municipal landfill. a) Data standard deviation recalculated for each quadrupole and displayed in its respective pseudo-section position. b) Results from the non-corrected inversion shown just for only three months out of the twenty, highlighting the low resistivity anomaly caused by the warmer temperatures (RATIO_3, RATIO_6). c) Result from the ARES inversion correcting for T_{ATM} effect.

No direct measurements of the thermal diffusivity parameter are available for the landfill body. However, to assess the representativeness of the retrieved α_{inv} , an additional test is conducted. In this analysis the same four lines previously modelled are split and modelled independently with the ARES scheme. As previously described, the ARES scheme assumes a single thermal diffusivity for the investigated medium, implying that the shallow thermal characteristics lie within a certain range of variability, despite potential waste heterogeneity. This assumption is supported by the results of the present analysis, extensively reported in APPENDIX B: NUMERICAL STABILITY OF THE THERMAL MODELLING WITH IMPLICATIONS FOR ARES INVERSION SCHEME, where the independent ARES inversions retrieved an average thermal diffusivity of $(2.53 \pm 0.6)E-06$ m²/s across the four survey lines. These results indicate a relatively narrow variability in the estimated thermal diffusivity within the acquisition matrix. Further support comes from the comparison between the α values from the independent ARES inversions (Table Appendix 1, APPENDIX B: NUMERICAL STABILITY OF THE THERMAL MODELLING WITH IMPLICATIONS FOR ARES INVERSION SCHEME) and the value obtained from the inversion of the full dataset ($3.53E-06$ m²/s).

Regarding the accuracy of the thermal diffusivity estimate, the literature reports a quite wide range of values for MSW (e.g., Hanson et al., 2010; Faitli et al., 2015), largely due to the highly variable nature of waste types and conditions. The retrieved alpha value of $3.53E-06$ m²/s lies well within the range identified for this type of structure. For instance, Tansel (2023) reports values ranging between $1.0E-7$ and $1.0E-6$ m²/s for waste composed, for example, of bricks, soil, dry plywood, cardboard, and animal organic waste. As stated earlier, the primary goal of this 20-month monitoring effort is to spatially and temporally identify the most productive biogas areas within the landfill and track their development. For this purpose, Figure 35 presents the same inversion results as Figure 34, but this time showing the resistivity ratios across the entire 3D volume for each of the twenty months. Figure 35 displays the ratios from the non-corrected models (Figure 35a) and from the ARES corrected models (Figure 35b). The 3D ratios are obtained by dividing the second model (RES_0, FEB_19) by the subsequent ones instead of the initial one (JAN_19), preferring it as baseline due to data quality considerations. In the ratio models of Figure 35, decreased resistivity is shown by values greater than one (blue anomalies) and increased resistivity by values less than one (red anomalies). The ratio models are

finally displayed by filtering the volumes to retain only the zones exhibiting resistivity changes greater than 10%.

The analysis of Figure 35a shows that without temperature correction, interpreting the resistivity models over time is unfeasible. A persistent shallow anomaly in the model ratios across most of the temporal models in the experiment (from MAY_19 to JAN_20 and from MAY_20 to AUG_20), masking any other signal. Conversely, the ratios from the ARES inverted model (Figure 35b) confirm the findings of Figure 34 demonstrating effective compensation of the T_{ATM} effect in the models and enabling the identification of resistivity anomalies independent of temperature effects. Specifically, a seasonal pattern emerges from the resistivity models, with a lower resistivity anomaly developing during the warmer season and decreasing back in the winter months. Additionally, a high resistivity anomaly begins to develop in December 2019, peaks in April 2020, and the gradually decreases toward the end of the monitoring period.

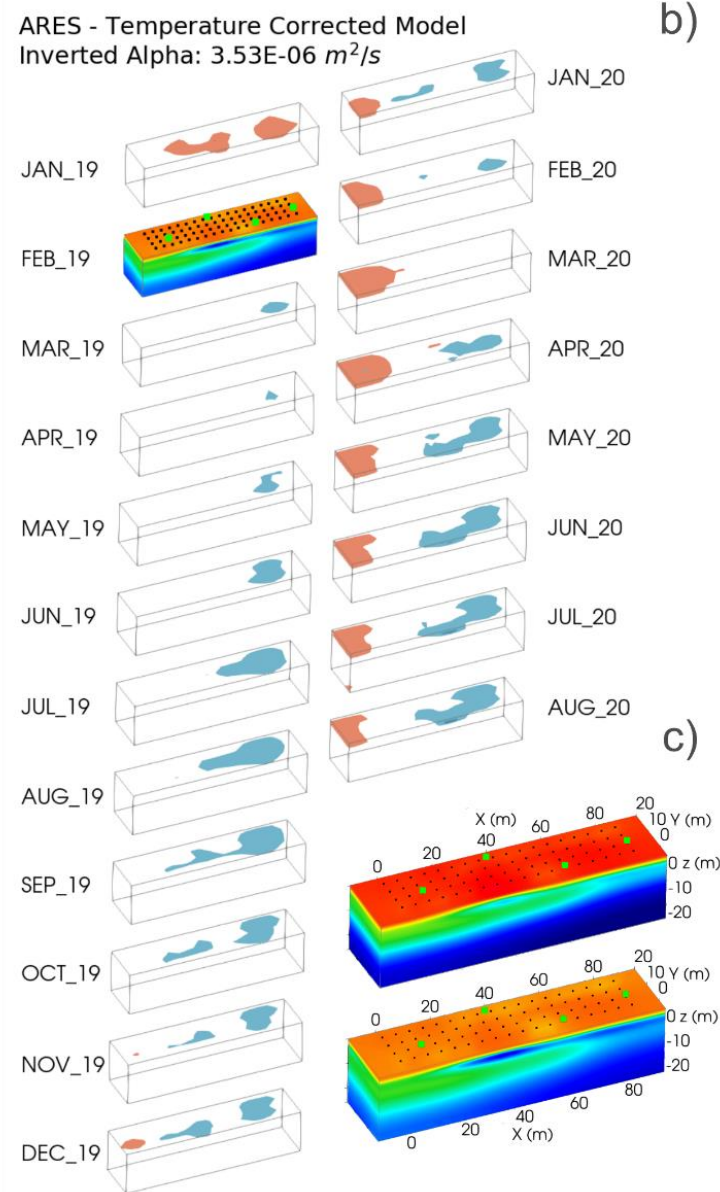
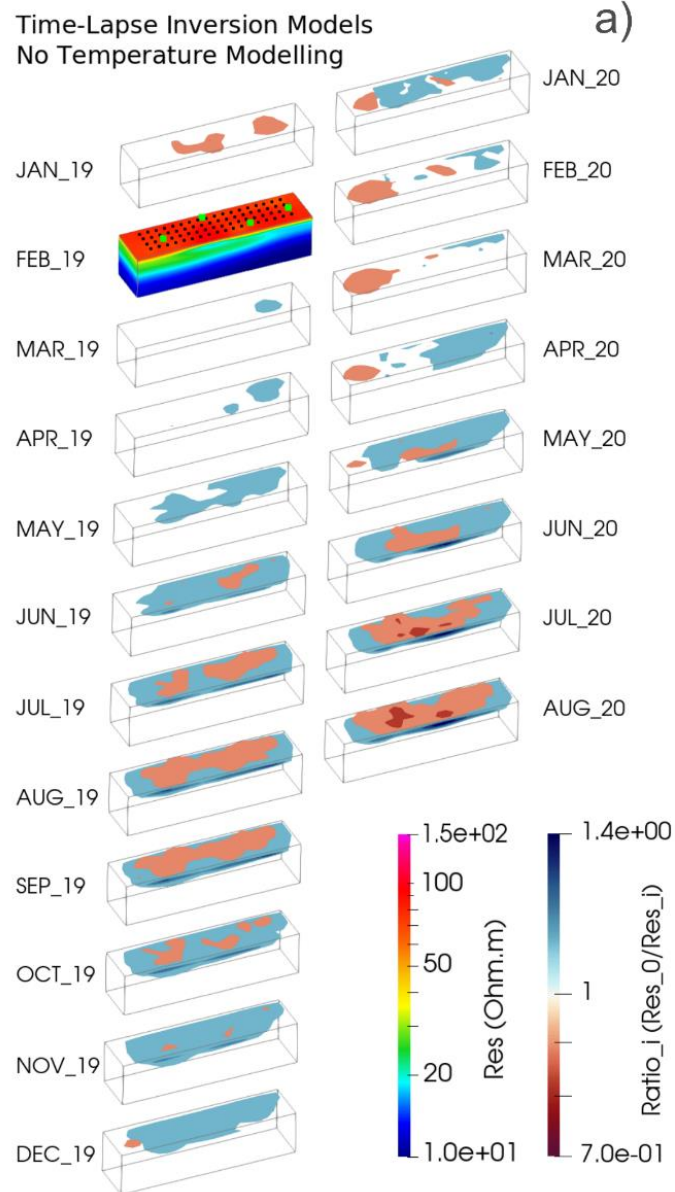


Figure 35: 3D ratios obtained from the classic time-lapse (a) and ARES inversion schemes (b). Ratios are computed by dividing the second model in time (FEB_19, RES_0) by the others. The FEB_19 model displays the resistivity value distribution, along with electrode (black points) and biogas pumping-wells positions (green points).

MODEL INTERPRETATION

The time-lapse modelling conducted using the ARES inversion scheme, reveals a clear seasonal evolution over the 20-month monitoring period (Figure 35b). The development of low-resistivity anomalies during the warmer seasons correlates with the methanogenic bacteria reaching their optimal physiological temperature under such temperatures (Moreira et al., 2014; Chai et al., 2016). This also aligns with the landfill biogas production data (Figure 36), further supporting the interpretation of these anomalies as indicative of intensified methanogenetic activity.

The primary electrical signature of the methanogenetic process can be expected as a persistent low-resistivity anomaly, consistently with the exothermic nature of this biochemical reaction (Bingemer and Crutzen, 1987; Moreira et al., 2015; Themelis and Ulloa, 2007) and its release of secondary reaction products such as water with high ionic concentrations. Given that, for the interpretations it is important to recall the presence of the landfill waterproof cover, which prevents water infiltration and excludes rainfall from the interpretations. Additionally, the continuous operation of the pumping-well network actively removes gases from the waste body, preventing their accumulation under the cover, which could otherwise have led to increased resistivity.

Therefore, the biochemical-induced temperature increase is considered the primary source of the low-resistivity anomaly observed in the models. To further validate these variations as indicators of productive biogas zones, their volumes (Figure 36) are calculated across seasons and compared with the biogas pumping trends. Figure 36 reports the daily biogas extraction trend (orange line) for the entire landfill during most of the geophysical monitoring period. This cumulative volume represents the biogas extracted from wells distributed throughout the landfill, thus reflecting a broader trend of biogas production in comparison to the fraction aimed to be detected by our geophysical matrix (see Figure 33). In any case, this global trend is considered representative even for smaller areas. Moreover, when interpreting the pumping data, it is important to consider that, from a management perspective, the total methane extracted from the landfill must remain constant throughout the year. Consequently, higher pumping rates are applied during periods of lower biogas production, typically in winter months when bacterial activity is lower. Conversely, lower pumping rates are sufficient during the summer, when the enhanced methanogenesis leads to higher

methane concentration in the extracted biogas. As a result, during the warmer months, a smaller volume of biogas needs to be extracted to meet the required methane threshold, as each unit contains a higher methane content.

This pattern found great correspondence with the geophysical analysis (Figure 36), where higher pumping rates (orange line, winter months) aligning with the smaller low-resistivity volumes detected by the geoelectrical survey, and vice versa. Refer to Table 10 for a comprehensive quantitative analysis covering the entire monitoring period.

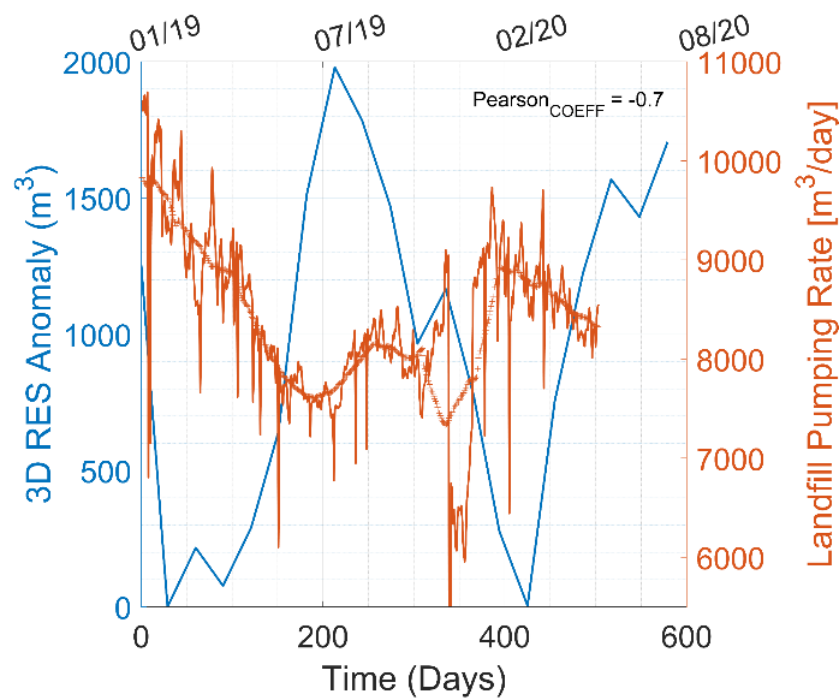


Figure 36: Biogas extraction volumes from the entire landfill over time (orange line) and resistivity anomaly volumes (blue line) detected in the geophysical matrix within the studied landfill sub-volume are shown. A Pearson correlation coefficient of -0.7, calculated after smoothing the pumping data with a 60-day moving average (orange cross-marks)..

Table 10: Cumulative monthly biogas extraction from the landfill pumping system (second column). Pumping data from June to August 2020 are unavailable. Resistivity anomaly volumes detected within the landfill area under study (third column). The volume for February 2019 is not provided, as this model served as the baseline for computing all other time step ratios.

	Monthly cum. biogas pump.	Res. anomaly volume [m ³]
01/01/2019 (DAY_0)	3.04E+05	1.26E+03
01/02/2019 (DAY 30)	2.63E+05	N.D.
01/03/2019 (DAY 60)	2.78E+05	2.16E+02
01/04/2019 (DAY 90)	2.64E+05	7.71E+01
01/05/2019 (DAY 120)	2.50E+05	2.91E+02
01/06/2019 (DAY 150)	2.32E+05	6.42E+02
01/07/2019 (DAY 180)	2.34E+05	1.51E+03
01/08/2019 (DAY 210)	2.44E+05	1.98E+03
01/09/2019 (DAY 240)	2.46E+05	1.78E+03
01/10/2019 (DAY 270)	2.50E+05	1.47E+03
01/11/2019 (DAY 300)	2.42E+05	9.66E+02
01/12/2019 (DAY 330)	2.06E+05	1.17E+03
01/01/2020 (DAY 360)	2.32E+05	7.71E+02
01/02/2020 (DAY 390)	2.13E+05	2.77E+02
01/03/2020 (DAY 420)	2.24E+05	3.77E+00
01/04/2020 (DAY 450)	2.10E+05	7.56E+02
01/05/2020 (DAY 480)	1.16E+05	1.22E+03
01/06/2020 (DAY 510)	N.D.	1.57E+03
01/07/2020 (DAY 540)	N.D.	1.43E+03
01/08/2020 (DAY 570)	N.D.	1.71E+03

Based on the strong negative correlation between the two trends (Figure 36, Pearson coefficient: -0.7, 60 days of smoothing window on the biogas pumping data), the low-resistivity anomalies (Figure 35b), are now considered validated as resulting from enhanced methanogenic processes. Hence, they can be used to precise spatial

identification of landfill portions where the waste composition seasonally fosters higher bacterial reaction rates.

For completeness, it's important to note that the pumping trends in Figure 36 shows a significant decrease in volumes in the second winter seasons of the monitoring (from Day 330). This reduction corresponds with the landfill's closure followed by a gradual decrease in the pumping rates. Therefore, this decrease isn't directly related to the landfill methane production. Nonetheless, the increased pumping demand during the winter season remains evident.

As a conclusion to this section, it is worth underscoring that neither quantitative nor qualitative interpretations would have been possible without effective T_{ATM} correction. In this specific application, these results highlight the potential to establish new practices for studying municipal landfills, tracking waste evolution over time, monitoring biogas production, and ultimately supporting effective management solutions.

2.1.2.6 CONCLUSIONS

In this work, we developed an innovative inversion scheme, named ARES, designed to support geophysical ERT monitoring surveys impacted by atmospheric temperature effects and lacking ground temperature data. This correction scheme not only represents a tool for modelling temperature effects in newly-acquired galvanic monitoring but also enables the recovery and reanalysis of past ERT monitoring datasets rendered unfeasible due to temperature-related effects.

In this work, we highlighted the significant influence of atmospheric temperature on resistivity data in monitoring experiments, emphasizing how temperature-induced electrical anomalies can exceed those associated with the target phenomena, potentially leading to misinterpretations or completely preventing analysis.

The correction scheme proposed compensates for atmospheric temperature effects on resistivity models by incorporating the thermal diffusivity of the subsoil as an inversion parameter. The ARES inversion performs the temperature modelling in the ground using atmospheric temperature data, such as those from the nearest weather station, alongside other boundary conditions, within a time-lapse framework. After a comprehensive assessment of the ARES scheme in a synthetic environment, its application to a real case study is presented, confirming excellent results in correcting atmospheric temperature

effects in the models. The field study investigated biogas production dynamics over a landfill during a 20-month experiment, where strong temperature effects influenced the data throughout the entire monitoring period. No ground temperature measurements were available at the site, and the target biochemical anomalies were indistinguishable before the ARES correction due to atmospheric temperature effects overshadowing. The ARES correction provided reliable thermal diffusivity values for the landfill site. Moreover, the geophysical results were validated with independent ancillary data, confirming the volumetric analysis and enabling new management decisions, such as drilling new extraction wells in the landfill portions identified as the most productive for biogas.

Notably, from a modelling perspective, since the primary resistivity anomaly was attributed to an exothermic reaction (methanogenesis), the ARES correction effectively removed atmospheric temperature influences while preserving the underlying biologically induced thermal anomalies. This confirms the suitability of the ARES scheme for monitoring strategies based on thermal tracing, as it successfully filters out unwanted atmospheric effects while retaining the thermal anomalies of interest.

The ARES scheme offers a technical solution for a wide range of monitoring studies and provides also a cost-effective, logistically simplified alternative for ERT monitoring. As an outlook, further developments will include the definition of model subregions with varying thermal properties, allowing for more precise handling of geological heterogeneity when needed.

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REFERENCES

Arps, J.J., 1953. The Effect of Temperature on the Density and Electrical Resistivity of Sodium Chloride Solutions. *Journal of Petroleum Technology* 5, 17–20.
<https://doi.org/10.2118/953327-G>

- Auken, E., Christiansen, A.V., Kirkegaard, C., Fiandaca, G., Schamper, C., Behroozmand, A.A., Binley, A., Nielsen, E., Effersø, F., Christensen, N.B., Sørensen, K., Foged, N., Vignoli, G., 2015. An overview of a highly versatile forward and stable inverse algorithm for airborne, ground-based and borehole electromagnetic and electric data. *Exploration Geophysics* 46, 223–235. <https://doi.org/10.1071/EG13097>
- Bingemer, H.G., Crutzen, P.J., 1987. The production of methane from solid wastes. *J. Geophys. Res.* 92, 2181–2187. <https://doi.org/10.1029/JD092iD02p02181>
- Binley, A., Winship, P., West, L.J., Pokar, M., Middleton, R., 2002a. Seasonal variation of moisture content in unsaturated sandstone inferred from borehole radar and resistivity profiles. *Journal of Hydrology* 267, 160–172. [https://doi.org/10.1016/S0022-1694\(02\)00147-6](https://doi.org/10.1016/S0022-1694(02)00147-6)
- Binley, A., Winship, P., West, L.J., Pokar, M., Middleton, R., 2002b. Seasonal variation of moisture content in unsaturated sandstone inferred from borehole radar and resistivity profiles. *Journal of Hydrology* 267, 160–172. [https://doi.org/10.1016/S0022-1694\(02\)00147-6](https://doi.org/10.1016/S0022-1694(02)00147-6)
- Boyd, J., Chambers, J., Wilkinson, P., Peppas, M., Watlet, A., Kirkham, M., Jones, L., Swift, R., Meldrum, P., Uhlemann, S., Binley, A., 2021. A linked geomorphological and geophysical modelling methodology applied to an active landslide. *Landslides* 18, 2689–2704. <https://doi.org/10.1007/s10346-021-01666-w>
- Brunet, P., Clément, R., Bouvier, C., 2010. Monitoring soil water content and deficit using Electrical Resistivity Tomography (ERT) – A case study in the Cevennes area, France. *Journal of Hydrology* 380, 146–153. <https://doi.org/10.1016/j.jhydrol.2009.10.032>
- Cassiani, G., Bruno, V., Villa, A., Fusi, N., Binley, A.M., 2006. A saline trace test monitored via time-lapse surface electrical resistivity tomography. *Journal of Applied Geophysics* 59, 244–259. <https://doi.org/10.1016/j.jappgeo.2005.10.007>
- Cassiani, G., Godio, A., Stocco, S., Villa, A., Deiana, R., Frattini, P., Rossi, M., 2009. Monitoring the hydrologic behaviour of a mountain slope via time-lapse electrical resistivity tomography. *Near Surface Geophysics* 7, 475–486. <https://doi.org/10.3997/1873-0604.2009013>

Caterina, D., Flores Orozco, A., Nguyen, F., 2017. Long-term ERT monitoring of biogeochemical changes of an aged hydrocarbon contamination. *Journal of Contaminant Hydrology* 201, 19–29. <https://doi.org/10.1016/j.jconhyd.2017.04.003>

Chai, X., Tonjes, D.J., Mahajan, D., 2016. Methane emissions as energy reservoir: Context, scope, causes and mitigation strategies. *Progress in Energy and Combustion Science* 56, 33–70. <https://doi.org/10.1016/j.pecs.2016.05.001>

Chambers, J.E., Gunn, D.A., Wilkinson, P.B., Meldrum, P.I., Haslam, E., Holyoake, S., Kirkham, M., Kuras, O., Merritt, A., Wragg, J., 2014. 4D electrical resistivity tomography monitoring of soil moisture dynamics in an operational railway embankment. *Near Surface Geophysics* 12, 61–72. <https://doi.org/10.3997/1873-0604.2013002>

Christensen, T.H., Kjeldsen, P., Albrechtsen, H., Heron, G., Nielsen, P.H., Bjerg, P.L., Holm, P.E., 1994. Attenuation of landfill leachate pollutants in aquifers. *Critical Reviews in Environmental Science and Technology* 24, 119–202. <https://doi.org/10.1080/10643389409388463>

Dahlin, T., Zhou, B., 2004. A numerical comparison of 2D resistivity imaging with 10 electrode arrays. *Geophysical Prospecting* 52, 379–398. <https://doi.org/10.1111/j.1365-2478.2004.00423.x>

Daily, W., Ramirez, A., LaBrecque, D., Nitao, J., 1992. Electrical resistivity tomography of vadose water movement. *Water Resources Research* 28, 1429–1442. <https://doi.org/10.1029/91WR03087>

Dalla Santa, G., Galgaro, A., Sassi, R., Cultrera, M., Scotton, P., Mueller, J., Bertermann, D., Mendrinós, D., Pasquali, R., Perego, R., Pera, S., Di Sipio, E., Cassiani, G., De Carli, M., Bernardi, A., 2020. An updated ground thermal properties database for GSHP applications. *Geothermics* 85, 101758. <https://doi.org/10.1016/j.geothermics.2019.101758>

De Vasconcelos, S.S., Batista, J.D.C., Leal, L.R.B., 2023. Multiple geophysical methods for mapping the geometry, leachate and biogas in old waste dumps in Northeast Brazil. <https://doi.org/10.21203/rs.3.rs-3340776/v1>

- Descloitres, M., Ruiz, L., Sekhar, M., Legchenko, A., Braun, J., Mohan Kumar, M.S., Subramanian, S., 2008. Characterization of seasonal local recharge using electrical resistivity tomography and magnetic resonance sounding. *Hydrological Processes* 22, 384–394. <https://doi.org/10.1002/hyp.6608>
- Doetsch, J., Linde, N., Vogt, T., Binley, A., Green, A.G., 2012. Imaging and quantifying salt-tracer transport in a riparian groundwater system by means of 3D ERT monitoring. *GEOPHYSICS* 77, B207–B218. <https://doi.org/10.1190/geo2012-0046.1>
- Faitli, J., Magyar, T., Erdélyi, A., Murányi, A., 2015. Characterization of thermal properties of municipal solid waste landfills. *Waste Management* 36, 213–221. <https://doi.org/10.1016/j.wasman.2014.10.028>
- Fiandaca, G., Christiansen, A.V., Auken, E., 2015. Depth of Investigation for Multi-parameters Inversions 2015, 1–5. <https://doi.org/10.3997/2214-4609.201413797>
- Fiandaca, Gianluca, Doetsch, J., Vignoli, G., Auken, E., 2015. Generalized focusing of time-lapse changes with applications to direct current and time-domain induced polarization inversions. *Geophysical Journal International* 203, 1101–1112. <https://doi.org/10.1093/gji/ggv350>
- French, H., Binley, A., 2004. Snowmelt infiltration: monitoring temporal and spatial variability using time-lapse electrical resistivity. *Journal of Hydrology* 297, 174–186. <https://doi.org/10.1016/j.jhydrol.2004.04.005>
- Glendinning, S., Hughes, P., Helm, P., Chambers, J., Mendes, J., Gunn, D., Wilkinson, P., Uhlemann, S., 2014. Construction, management and maintenance of embankments used for road and rail infrastructure: implications of weather induced pore water pressures. *Acta Geotech.* 9, 799–816. <https://doi.org/10.1007/s11440-014-0324-1>
- Glover, P.W.J., 2015. Geophysical Properties of the Near Surface Earth: Electrical Properties, in: *Treatise on Geophysics*. Elsevier, pp. 89–137. <https://doi.org/10.1016/B978-0-444-53802-4.00189-5>
- Hanson, J.L., Yeşiller, N., Oettle, N.K., 2010. Spatial and Temporal Temperature Distributions in Municipal Solid Waste Landfills. *J. Environ. Eng.* 136, 804–814. [https://doi.org/10.1061/\(ASCE\)EE.1943-7870.0000202](https://doi.org/10.1061/(ASCE)EE.1943-7870.0000202)

- Hayley, K., Bentley, L.R., Gharibi, M., 2009. Time-lapse electrical resistivity monitoring of salt-affected soil and groundwater. *Water Resources Research* 45, 2008WR007616. <https://doi.org/10.1029/2008WR007616>
- Hayley, K., Bentley, L.R., Gharibi, M., Nightingale, M., 2007. Low temperature dependence of electrical resistivity: Implications for near surface geophysical monitoring. *Geophysical Research Letters* 34, 2007GL031124. <https://doi.org/10.1029/2007GL031124>
- Hayley, K., Bentley, L.R., Pidlisecky, A., 2010. Compensating for temperature variations in time-lapse electrical resistivity difference imaging. *GEOPHYSICS* 75, WA51–WA59. <https://doi.org/10.1190/1.3478208>
- Hayley, K., Pidlisecky, A., Bentley, L.R., 2011. Simultaneous time-lapse electrical resistivity inversion. *Journal of Applied Geophysics* 75, 401–411. <https://doi.org/10.1016/j.jappgeo.2011.06.035>
- Hermans, T., Wildemeersch, S., Jamin, P., Orban, P., Brouyère, S., Dassargues, A., Nguyen, F., 2015. Quantitative temperature monitoring of a heat tracing experiment using cross-borehole ERT. *Geothermics* 53, 14–26. <https://doi.org/10.1016/j.geothermics.2014.03.013>
- Jodry, C., Palma Lopes, S., Fargier, Y., Sanchez, M., Côte, P., 2019. 2D-ERT monitoring of soil moisture seasonal behaviour in a river levee: A case study. *Journal of Applied Geophysics* 167, 140–151. <https://doi.org/10.1016/j.jappgeo.2019.05.008>
- Johnson, T.C., Versteeg, R.J., Day-Lewis, F.D., Major, W., Lane, J.W., 2015. Time-Lapse Electrical Geophysical Monitoring of Amendment-Based Biostimulation. *Groundwater* 53, 920–932. <https://doi.org/10.1111/gwat.12291>
- Karaoulis, M., Revil, A., Werkema, D.D., Minsley, B.J., Woodruff, W.F., Kemna, A., 2011a. Time-lapse three-dimensional inversion of complex conductivity data using an active time constrained (ATC) approach: Time-lapse complex conductivity imaging. *Geophysical Journal International* 187, 237–251. <https://doi.org/10.1111/j.1365-246X.2011.05156.x>
- Karaoulis, M.C., Kim, J.-H., Tsourlos, P.I., 2011b. 4D active time constrained resistivity inversion. *Journal of Applied Geophysics* 73, 25–34. <https://doi.org/10.1016/j.jappgeo.2010.11.002>

- Kim, J.-H., Yi, M.-J., Park, S.-G., Kim, J.G., 2009. 4-D inversion of DC resistivity monitoring data acquired over a dynamically changing earth model. *Journal of Applied Geophysics* 68, 522–532. <https://doi.org/10.1016/j.jappgeo.2009.03.002>
- LaBrecque, D.J., Ramirez, A.L., Daily, W.D., Binley, A.M., Schima, S.A., 1996. ERT monitoring of environmental remediation processes. *Meas. Sci. Technol.* 7, 375–383. <https://doi.org/10.1088/0957-0233/7/3/019>
- LaBrecque, D.J., Yang, X., n.d. Difference Inversion of ERT Data: a Fast Inversion Method for 3-D In Situ Monitoring. *Journal of Environmental and Engineering Geophysics*.
- Last, B.J., Kubik, K., 1983. Compact gravity inversion. *GEOPHYSICS* 48, 713–721. <https://doi.org/10.1190/1.1441501>
- Loke, M.H., Dahlin, T., Rucker, D.F., 2014. Smoothness-constrained time-lapse inversion of data from 3D resistivity surveys. *Near Surface Geophysics* 12, 5–24. <https://doi.org/10.3997/1873-0604.2013025>
- Luo, Z., Guan, H., Zhang, X., 2019. The temperature effect and correction models for using electrical resistivity to estimate wood moisture variations. *Journal of Hydrology* 578, 124022. <https://doi.org/10.1016/j.jhydrol.2019.124022>
- Mendonça, C.A., Doherty, R., Amaral, N.D., McPolin, B., Larkin, M.J., Ustra, A., 2015. Resistivity and induced polarization monitoring of biogas combined with microbial ecology at a brownfield site. *Interpretation* 3, SAB43–SAB56. <https://doi.org/10.1190/INT-2015-0057.1>
- Miller, C.R., Routh, P.S., Brosten, T.R., McNamara, J.P., 2008. Application of time-lapse ERT imaging to watershed characterization. *GEOPHYSICS* 73, G7–G17. <https://doi.org/10.1190/1.2907156>
- Moreira, C., Castro, M., Gonsalez, A., Cavallari, F., Munhoz, T., Pereira, A., 2014. Comparative Analysis between Biogas Flow in Landfill and Electrical Resistivity Tomography in Rio Claro City, Brazil. *Journal of Geological Research* 2014, 1–7. <https://doi.org/10.1155/2014/845906>
- Moreira, C.A., De Castro, M.C.A.A., Carrazza, L.P., Cavallari, F., Helene, L.P.I., Machado, F.B., 2015. RELATIONSHIP BETWEEN BIOGAS PRODUCTION AND VARIATIONS IN ELECTRIC

RESISTIVITY IN LANDFILL OF RIO CLARO CITY, BRAZIL. *Rev. Bras. Geof.* 33.
<https://doi.org/10.22564/rbgf.v33i2.715>

Musgrave, H., Binley, A., 2011. Revealing the temporal dynamics of subsurface temperature in a wetland using time-lapse geophysics. *Journal of Hydrology* 396, 258–266. <https://doi.org/10.1016/j.jhydrol.2010.11.008>

Nasta, P., Boaga, J., Deiana, R., Cassiani, G., Romano, N., 2019. Comparing ERT- and scaling-based approaches to parameterize soil hydraulic properties for spatially distributed model applications. *Advances in Water Resources* 126, 155–167.
<https://doi.org/10.1016/j.advwatres.2019.02.014>

Oldenborger, G.A., Knoll, M.D., Routh, P.S., LaBrecque, D.J., 2007. Time-lapse ERT monitoring of an injection/withdrawal experiment in a shallow unconfined aquifer. *GEOPHYSICS* 72, F177–F187. <https://doi.org/10.1190/1.2734365>

Pellicer, X.M., Zarroca, M., Gibson, P., 2012. Time-lapse resistivity analysis of Quaternary sediments in the Midlands of Ireland. *Journal of Applied Geophysics* 82, 46–58.
<https://doi.org/10.1016/j.jappgeo.2012.02.009>

Portniaguine, O., Zhdanov, M.S., 1999. Focusing geophysical inversion images. *GEOPHYSICS* 64, 874–887. <https://doi.org/10.1190/1.1444596>

Ramirez, A., Daily, W., LaBrecque, D., Owen, E., Chesnut, D., 1993. Monitoring an underground steam injection process using electrical resistance tomography. *Water Resources Research* 29, 73–87. <https://doi.org/10.1029/92WR01608>

Rao, S., Lesparre, N., Flores-Orozco, A., Wagner, F., Kemna, A., Javaux, M., 2020. Imaging plant responses to water deficit using electrical resistivity tomography. *Plant Soil* 454, 261–281. <https://doi.org/10.1007/s11104-020-04653-7>

Rein, A., Hoffmann, R., Dietrich, P., 2004. Influence of natural time-dependent variations of electrical conductivity on DC resistivity measurements. *Journal of Hydrology* 285, 215–232. <https://doi.org/10.1016/j.jhydrol.2003.08.015>

Roberts, J.J., 2002. Electrical properties of microporous rock as a function of saturation and temperature. *Journal of Applied Physics* 91, 1687–1694.
<https://doi.org/10.1063/1.1430544>

- Sen, P.N., Goode, P.A., 1992. Influence of temperature on electrical conductivity on shaly sands. *GEOPHYSICS* 57, 89–96. <https://doi.org/10.1190/1.1443191>
- Sherrod, L., Sauck, W., Werkema, D.D., 2012. A Low-Cost, In Situ Resistivity and Temperature Monitoring System. *Groundwater Monitoring Rem* 32, 31–39. <https://doi.org/10.1111/j.1745-6592.2011.01380.x>
- Singha, K., Day-Lewis, F.D., Johnson, T., Slater, L.D., 2015. Advances in interpretation of subsurface processes with time-lapse electrical imaging. *Hydrological Processes* 29, 1549–1576. <https://doi.org/10.1002/hyp.10280>
- Steelman, C.M., Kennedy, C.S., Capes, D.C., Parker, B.L., 2017. Electrical resistivity dynamics beneath a fractured sedimentary bedrock riverbed in response to temperature and groundwater–surface water exchange. *Hydrol. Earth Syst. Sci.* 21, 3105–3123. <https://doi.org/10.5194/hess-21-3105-2017>
- Sullivan, N.A.L., Viezzoli, A., Fiandaca, G., 2024. EEMstudio: Process and Model Electric and Electromagnetic Data with a QGIS Plugin 2024, 1–5. <https://doi.org/10.3997/2214-4609.202420154>
- Tansel, B., 2023. Thermal properties of municipal solid waste components and their relative significance for heat retention, conduction, and thermal diffusion in landfills. *Journal of Environmental Management* 325, 116651. <https://doi.org/10.1016/j.jenvman.2022.116651>
- Themelis, N.J., Ulloa, P.A., 2007. Methane generation in landfills. *Renewable Energy* 32, 1243–1257. <https://doi.org/10.1016/j.renene.2006.04.020>
- Waxman, M.H., Thomas, E.C., 1972. Electrical Conductivities in Shaly Sands - I. The Relation Between Hydrocarbon Saturation and Resistivity Index; II. The Temperature Coefficient of Electrical Conductivity. Presented at the Fall Meeting of the Society of Petroleum Engineers of AIME, p. SPE-4094-MS. <https://doi.org/10.2118/4094-MS>

APPENDIX A: EFFECT OF ATMOSPHERIC TEMPERATURE ON APPARENT RESISTIVITY DATA

The supplemental figure reported below (Figure Appendix 1) expands on Figure 29 from the main text, providing additional insights into the effect of seasonal atmospheric temperature oscillations on resistivity data. Figure Appendix 1 presents real data collected over the landfill employing a galvanic geophysical system, described as a case study in Section 2.1.2.5, during the 20-month monitoring experiment. The geophysical system consisted of four galvanic parallel lines, each capable of independent measurement, which consistently recorded similar temperature-related effects over time (first to fourth column in Figure Appendix 1). The impact of seasonal temperature variations is most pronounced near the surface, gradually weakening with depth but remaining clearly detectable down to a pseudo-depth of approximately -15 meters (Figure Appendix 1, third row).

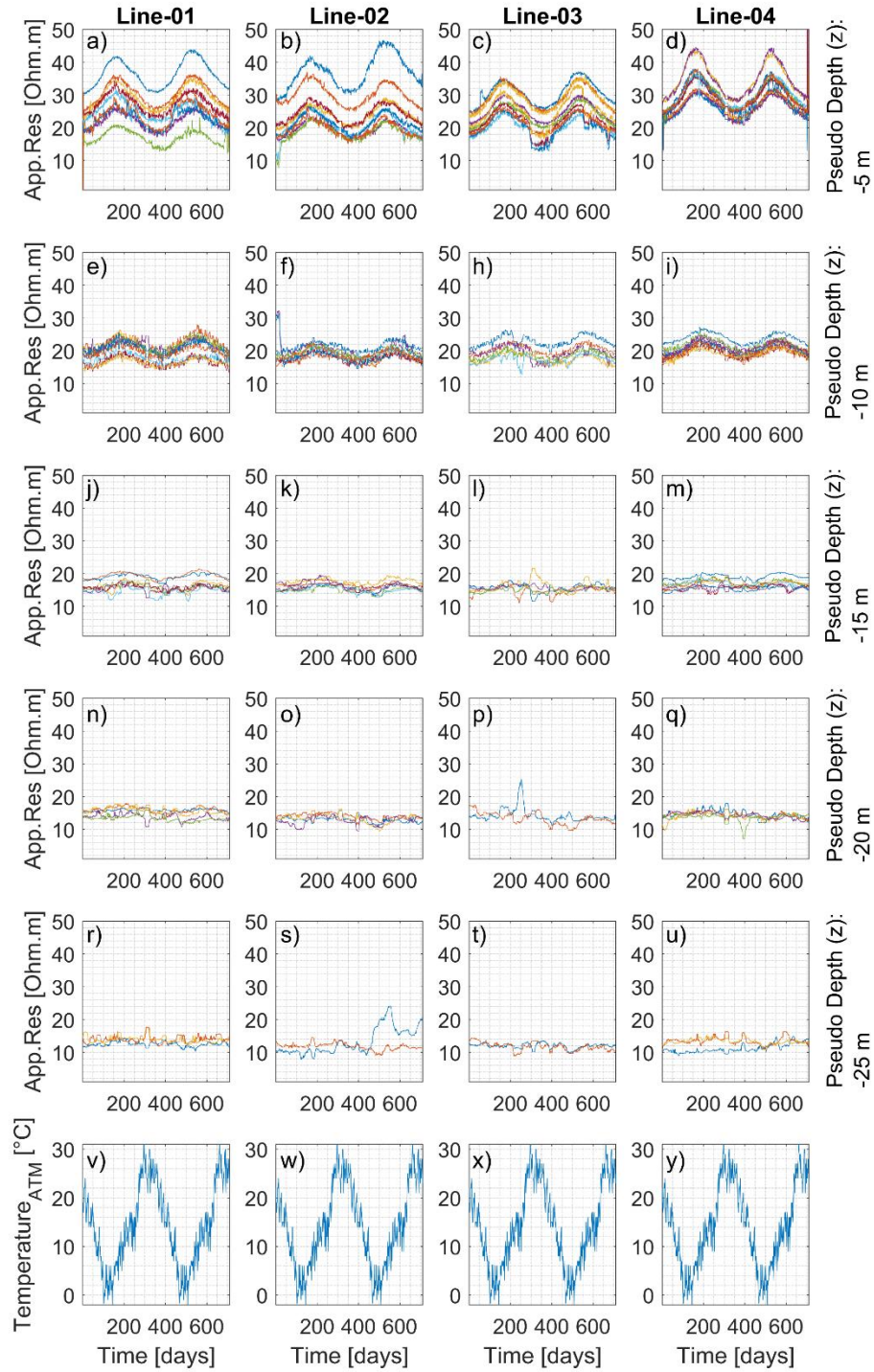


Figure Appendix 1: Atmospheric temperature effects influencing the apparent resistivity data recorded using a galvanic system placed over the top of a municipal landfill during a 20-month monitoring experiment. The panels show the daily data-sequence organized by the galvanic line used for acquisition (columns 1 to 4) and their respective pseudo-depths (rows 1 to 5). The bottom row displays the daily atmospheric temperature data recorded by the nearest weather station to the study site.

APPENDIX B: NUMERICAL STABILITY OF THE THERMAL MODELLING WITH IMPLICATIONS FOR ARES INVERSION SCHEME

As discussed in Section 2.1.2.3, the thermal modelling performed by the ARES inversion scheme requires solving the heat equation to model the underground propagation of the atmospheric temperature effect. To ensure numerical stability and convergence of the partial derivatives, the scheme employs the *CFL* coefficient (Eq. (46)), which must remain below 0.5. However, during practical ARES inversion processes, adjustments to the thermal diffusivity parameter (α) often increase the *CFL* value beyond 0.5, destabilizing the solution. To address this issue, the time interval between temperature steps is reduced through spline interpolation, which lowers the *CFL* value. As counter effect, since the ARES scheme requires solving the heat equation for all time steps between the first and the last one, the iteration times significantly extend as the step count to stabilize the solution increases.

This effect is clearly illustrated in the test presented in Figure Appendix 2, which was designed to assess the consistency of thermal diffusivity retrieval using the ARES inversion scheme on the field case described in Section 2.1.2.5. The test involved splitting the geophysical dataset into four separate survey lines and performing independent ARES inversions for each line. The results reported in Table Appendix 1 show thermal diffusivity values with an average of $(2.53 \pm 0.6) \text{E}-06 \text{ m}^2/\text{s}$, confirming the consistency of the ARES inversion scheme in estimating thermal diffusivity. These findings suggest a waste composition within the geophysical matrix characterized by relatively homogeneous thermal properties.

Table Appendix 1: Thermal diffusivity value (α) estimated by the ARES inversion for the four independent lines.

	Line01	Line02	Line03	Line04
ARES inverted α [m^2/s]	3.2e-06	3.0e-06	1.8e-06	2.1e-06

As previously said, Figure Appendix 2 also details the relationship between the alpha value and iteration time, highlighting the influence of this parameter on modelling duration. Notably, Figure Appendix 2a, c1–c4 shows that higher α values correlate with longer iteration times in the ARES correction protocol, due to the stabilization procedure. Figure Appendix 2b reveals that in all cases, the ARES inversion initially overshoots the α

value, resulting in extended computation times, before progressively decreasing and converging to a stable final value. As a practical note, when using the ARES protocol, it has been found effective to initialize the heat equation calculation well in advance of the first inversion time step in the monitoring experiment to ensure accurate retrieval of the temperature model.

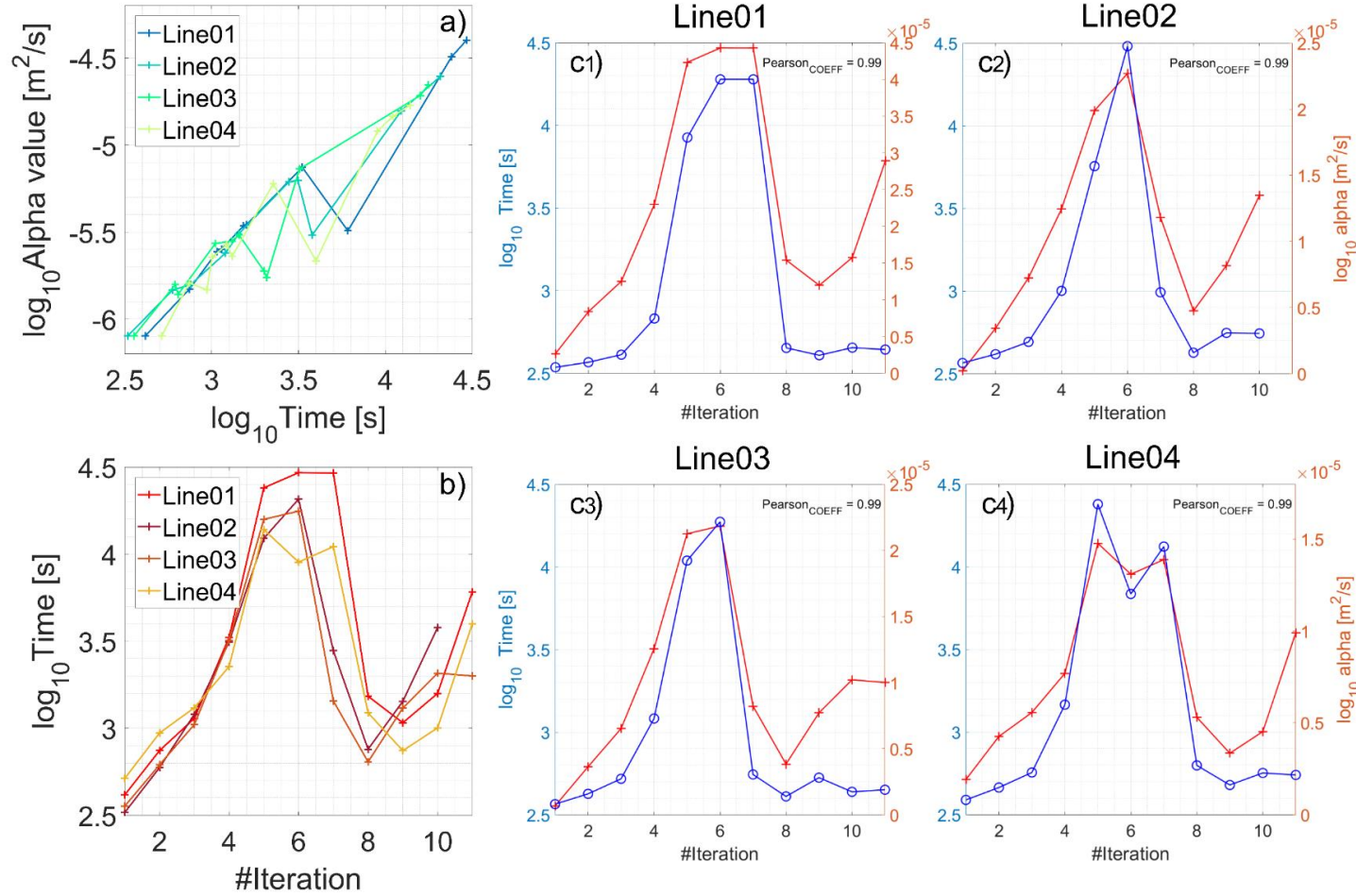


Figure Appendix 2: a) Iteration time of the ARES inversion versus the corresponding thermal diffusivity (α) value. Note how higher iteration times are associated with higher α values because of the stabilization procedure. b) Iteration time within the same ARES inversion process as primary result of the thermal diffusivity value. c1-c4) Iteration Time of independent line-inversions (blue line) in the ARES scheme overlapping with the corresponding iteration thermal diffusivity value (orange line). The Pearson correlation coefficient of the two trends is reported in each panel.

2.1.3 TEMPERATURE EFFECT ON ELECTROMAGNETIC MEASUREMENTS

The previous section provides a comprehensive description of the effects induced by temperature variations on galvanic data, and we can expect a similar impact on EM measurements, which also aim to characterize the subsurface in terms of electrical property distribution. This temperature effect, depending on the resolution of the EM system, can be significant when conducting EM monitoring experiments. However, this section will not focus on this aspect; instead, we will examine the potential influence of temperature variation on the calibration of EM systems (see Section 1.3.2).

To recall, the calibration of EM instruments ensures that the system is accurately defined in terms of its transfer function and properly calibrated. Since the reference model used to generate the calibration transient may have been characterized under different seasonal conditions than those during field calibration, it is essential to ensure the procedure remains unaffected by seasonal influences like temperature variations. In other words, we must ensure that the field-collected transient for calibration is assessed and, if needed, corrected against a reference signal adjusted for the temperature conditions at the time of calibration. This aim prompted further investigation into the effects of seasonal temperature variations on EM system responses. As discussed in Sections 2.1.2, temperature-induced fluctuations in electrical properties can penetrate to several meters below the surface, depending on factors such as the site location, the thermal diffusivity of the deposits and the geological lateral heterogeneity. More specifically, variations in electrical conductivity for a geological medium average around 2% per degree Celsius of temperature change (Hayley et al., 2007, Eq. (42)). Therefore, we decided to specifically investigate this effect on EM transients across different systems, subsoil models, and seasons (temperature models), with specific regards to instrument calibrations.

Temperature variations may lead to over- or under-compensation of signals calibrated under different conditions, resulting in erroneous corrections when attempting to adjust the on-site measured signal - influenced by seasonality - to the reference response. Figure 37 presents a synthetic experiment where different EM systems are tested by producing forward responses over different subsurface models, simulating six months of seasonal

temperature variations. This is accomplished following the same procedure detailed in Section 2.1.2.3 for galvanic measurements, adapted here for EM forward computations. The seasonal effect is included in the modelling by employing the heat diffusion equation, using a realistic literature thermal diffusivity value ($1.0\text{e-}07 \text{ m}^2/\text{s}$, see Dalla Santa et al., 2020) and incorporating real temperature data.

Two subsoil models are tested, one obtained for the Italian calibration site (Figure 10e, Section 1.2.1.4) as representative of a high-resistivity site, and a model from Foged et al., (2013) retrieved for the Danish calibration site which exhibits low resistivity characteristics.

Three EM systems are tested: tTEM, SkyTEM, and SkyTEM with system response (SSR) information obtained from high-altitude measurements rather than calculated by separately convolving different system components (e.g., transmitter waveform, receiver filters). With Specific regard to this section, The SSR approach offers the main advantage of performing on-time modeling with the possibility of using signal gates acquired during the current shutdown ramp. This allows for enhancing the near-surface sensitivity and resolution of the measured transients by adding earlier-times information closer to the beginning of the current turn-off.

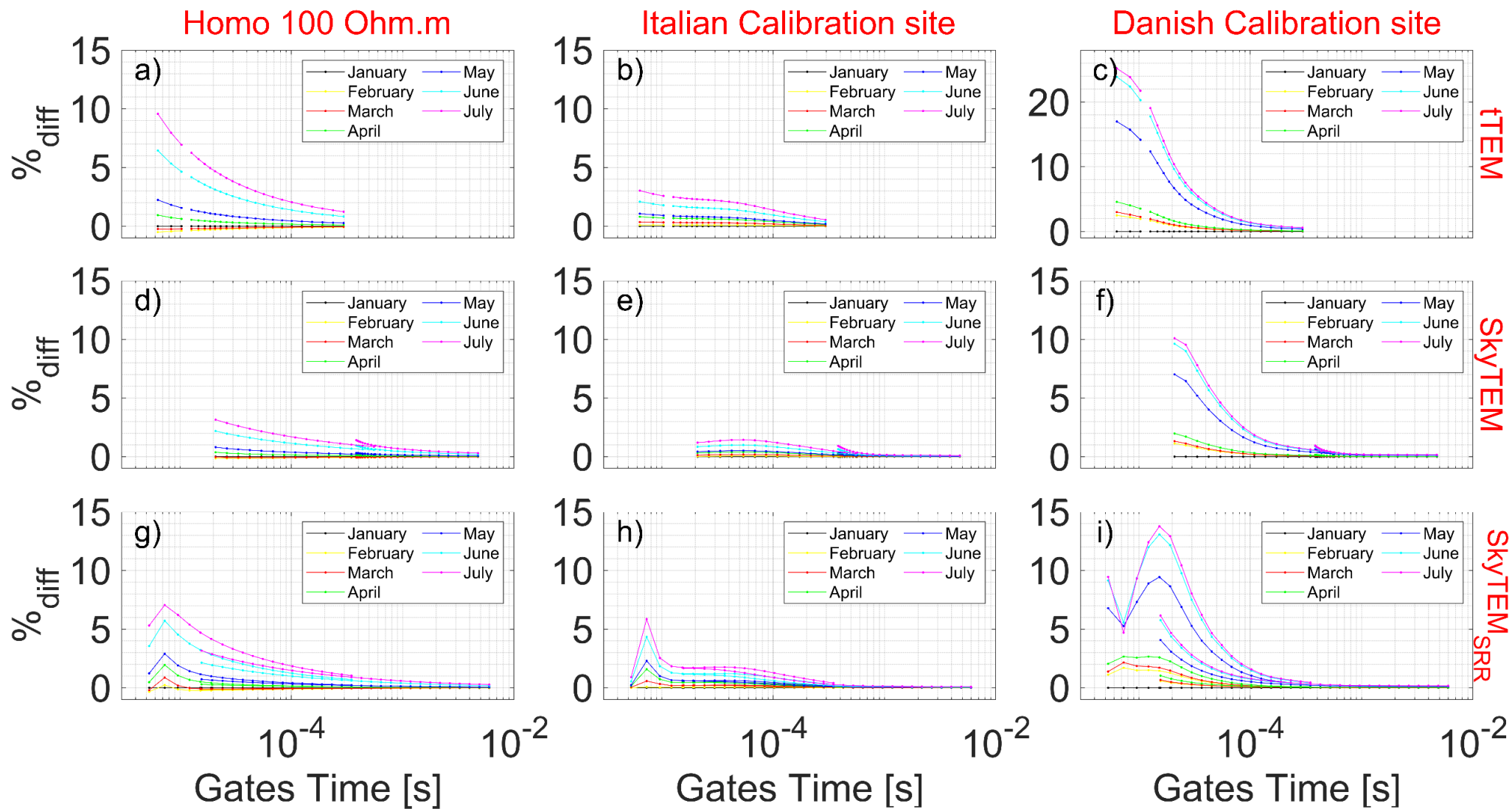


Figure 37: Synthetic experiment to investigate the effects of temperature-induced resistivity model variations on different EM systems. Thermal diffusivity value set to $1.0e-07 \text{ m}^2/\text{s}$ for the three sites. Homogeneous model (panels a, d, g); high-resistivity model (panels b, e, h); low-resistivity model (panels c, f, i). Different EM systems are evaluated: tTEM (panels a, b, c), SkyTEM (panels d, e, f), and SkyTEM with system response modelling (panels g, h, i).

The y-axis in the plot represents the percentage variation calculated between an initial forward response and subsequent ones, where the resistivity model has been progressively altered by different temperature effects. As a control, the black line in each plot shows the ratio between the initial model and itself. This experiment shows a significant impact of temperature-induced changes on all calculated transients, with particularly large variations observed as the temperature difference increases (e.g., January - July) and for the systems more sensitive to shallow variations (e.g., tTEM). Signal variations exceed 26% for the tTEM forward responses computed for July at the low-resistivity site (Figure 37c). Additionally, the temperature effect on transients consistently shows greater variations at the low-resistivity site. This, in a related consideration, reinforces the previously discussed importance of using high-resistivity sites for calibrating EM systems, which, additionally to their reduced susceptibility to temperature fluctuations, hide less system issues behind high signal levels.

Returning to the test results, these findings highlight the need to account for seasonal temperature variations during on-field EM system calibrations. This consideration is relevant given that the signal adjustments applied through time and level shifts (see Foged et al., 2013 and Figure 1) can lead to compensating for temperature-induced variations rather than actual changes in system characteristics. An example illustrating this concept is presented in Figure 38, where a calibration process is simulated between two tTEM responses. In this case, the reference signal represents the January response, while the “on-field” transient, used for system calibration, mimics data collected in July. The same three subsurface models as before are tested. The signals are presented in terms of apparent resistivity, using the following conversion:

$$Gate_i [Rho_{app}] = \frac{1}{\pi} \cdot \left(\frac{1}{20 \cdot |d_i|} \right)^{1/3} \cdot \left[\left(\frac{\mu_0}{t_i} \right) \right]^{1/3} \quad (51)$$

Where d_i is the gate value expressed in db/dt, μ_0 is the magnetic permeability of free space and t_i is the gate time.

Each panel displays the winter reference signal (blue line), the summer “under-calibration” signal (red line), and the post-calibration transient (green line). The time and level shift values used for calibration are indicated at the top of each panel. In all

experiments, the calibration successfully adjusted the temperature-affected signal to fall within the reference signal error bars.

To better describe the combined use of time and level shifts to align the under-calibration signal with the reference signal, we can refer to the case shown in Figure 38 for the Danish site. In this case, a level shift of 0.91 has been found sufficient to compensate for the signal variation induced by the transition from winter to summer conditions (approx. 25%, Figure 37, panel c) when coupled with a time shift of 5E-06 sec.

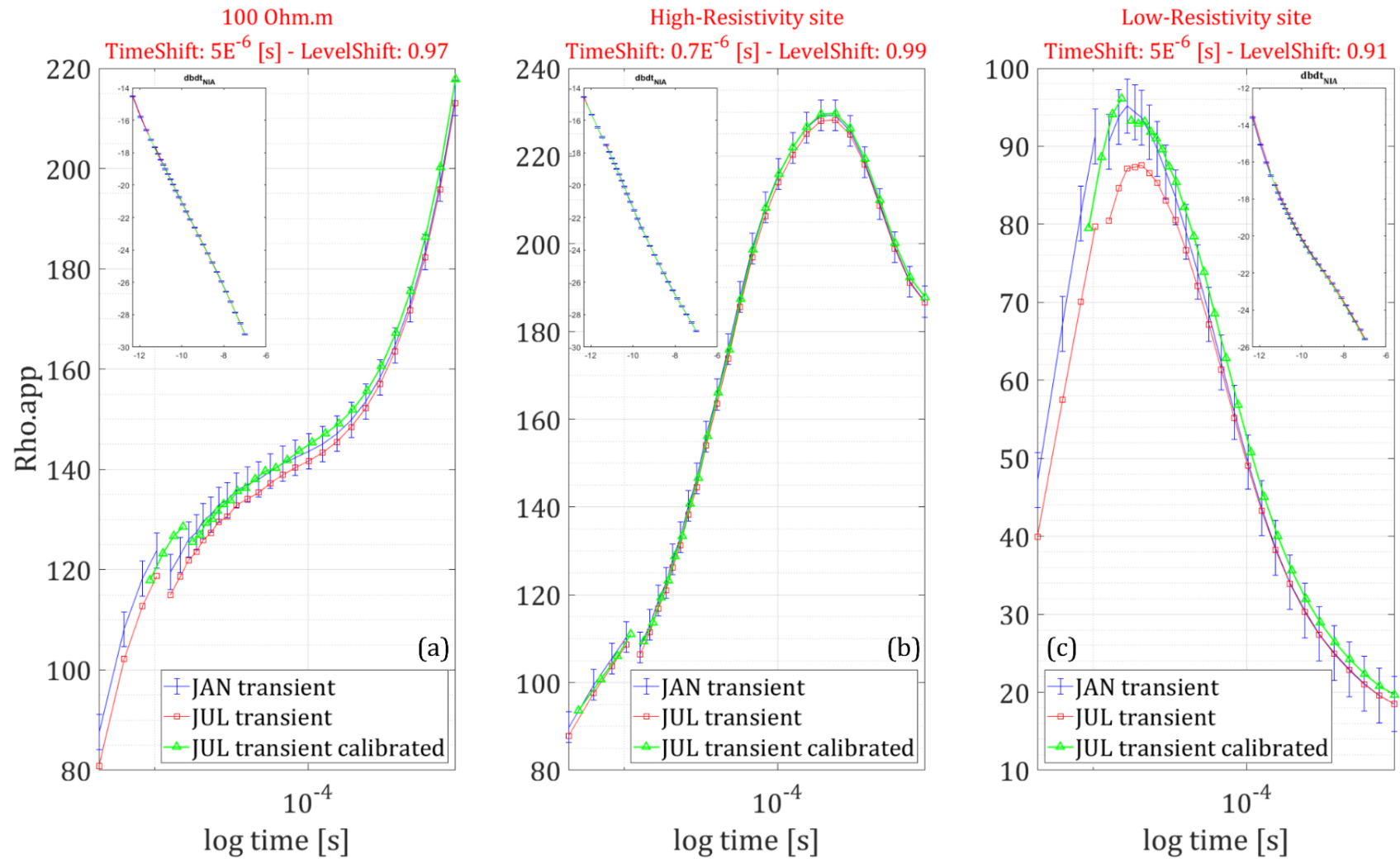


Figure 38: Calibration examples simulating the effect of temperature-induced resistivity variations on EM transients for three different subsurface models: homogeneous (panel a), high-resistivity (panel b), and low-resistivity (panel c). In each panel, the under-calibration transient (red line –simulated summer conditions) is shifted toward the reference transient (blue line – winter conditions) until within the latter error bars. Calibrated transient is shown as a green line, with time and level shifts indicated at the top of each panel. Respective db/dt signals are reported in the subplots.

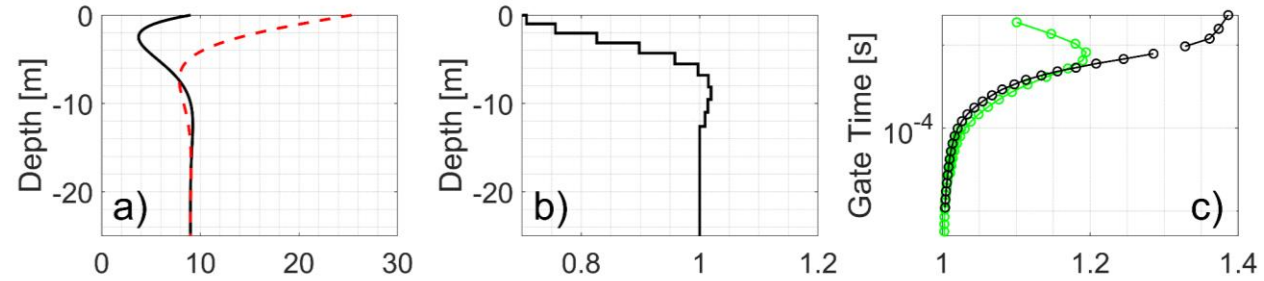
As the temperature effects observed on EM are significant in magnitude and would substantially impact the calibration procedure (and not only) of EM systems, we propose now an analysis of this effect that is reproducible without employing the ARES scheme provided by EEMverter.

To this end, the analytical solution of the heat equation (Eq. (44)) is considered for simulating and assessing the effect of different temperature models on the subsurface model of the Danish site, and subsequently on tTEM and SkyTEM data. The results of this analysis are presented in Figure 39, where three different values of thermal diffusivity are tested to perform thermal modelling at two different times representative of spring (panels a, d, g; black lines) and summer (red lines) conditions.

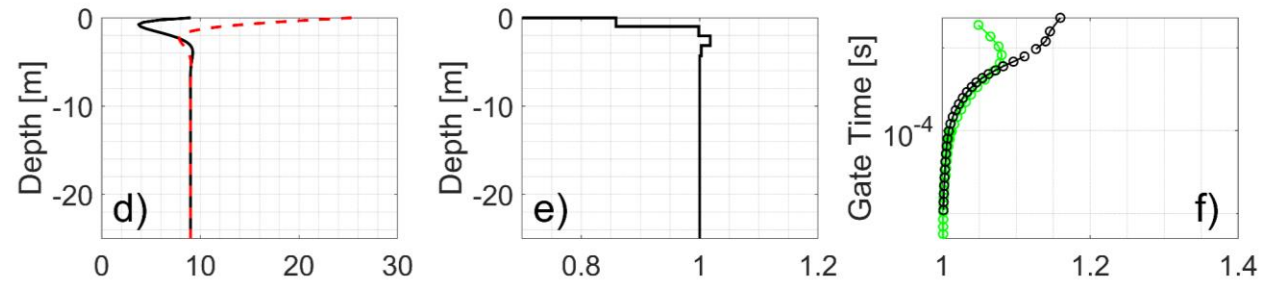
The thermal diffusivity range has been chosen as representative range of cohesive to granular sediments, with higher values corresponding to more cohesive materials (see Dalla Santa et al., 2020). For the analytical solution, the A_0 and T_0 parameters (Eq. (44)) were derived from real atmospheric temperature data measured in Denmark and set to 9.0 °C and 16.3 °C, respectively. The temperature-induced variations in subsurface resistivity for the different α are shown in panels b, e, and h of Figure 39, where layer-by-layer resistivity values are presented. These values have been modified using the formulation (Eq. (49)) proposed by Hayley et al., (2007) and employing the calculated temperature profiles. The analysis of this second columns show that moving from day 0 to day 90—i.e., from colder spring to warmer summer conditions—layer resistivity values tend to decrease. This reduction in resistivity depends on the value of thermal diffusivity: the higher α , the greater and deeper the temperature penetration, and consequently, the larger the changes observed in resistivity.

Computing now the forward responses for both the SkyTEM (Figure 39, panels c, f, i, green line) and tTEM (black line) it is appreciable how an increase in signal amplitude is observed moving from more to less resistive subsoils from day 0 to day 90. This trend is consistent with the typical behaviour of inductive EM systems, where lower subsurface resistivity results in stronger induced currents and, therefore, higher signal levels.

$$\alpha = 10^{-6} \text{ m}^2/\text{s}$$



$$\alpha = 10^{-7} \text{ m}^2/\text{s}$$



$$\alpha = 10^{-8} \text{ m}^2/\text{s}$$

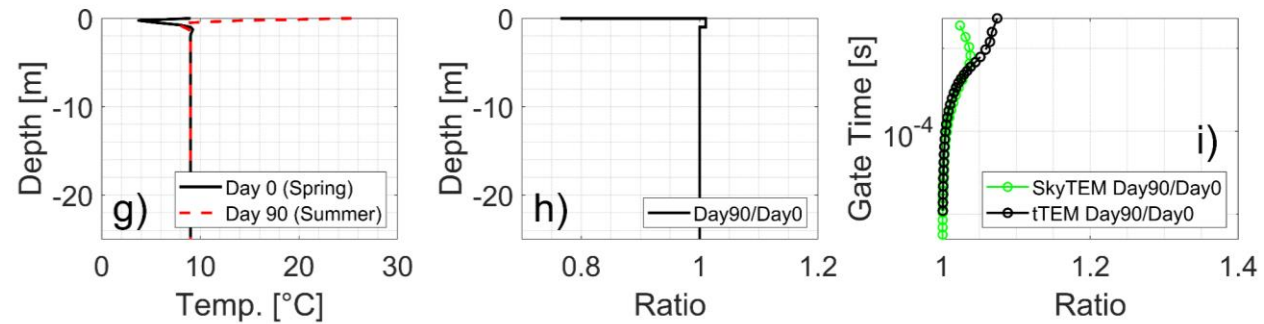


Figure 39: Effect of different thermal modelling obtained through analytical solutions employing different α values on: a, d, g) the propagation of the temperature effect with depth from spring (Day0) to summer (Day90) conditions; b, e, h) the subsoil resistivity distribution, where the results are displayed as the ratio between Day90 and Day0 subsoil models; c, f, i) the computation of 1D EM forward responses for SkyTEM (green line) and tTEM (black line) systems, where the results are shown as the ratio between Day90 and Day0 EM transients.

These results of this last analysis confirm the magnitude of the temperature effect on EM data presented first in Figure 37, and its potential impact on EM system calibration, discussed then in Figure 38, leading to some concluding considerations for this section:

- These results suggest that temperature-induced variations on EM signals fall well within the accuracy of the EM instruments.
- High Resistivity sites minimize temperature-related effect on the measured EM transients and are therefore preferable to low-resistivity site also from this perspective.
- Advancements in EM calibration procedures are needed to address seasonal temperature variations. A proposal in this regard is presented in Section 3.1, which offers suggestions for defining the most accurate subsoil model to reproduce the actual thermal response of a site.

Before reaching Section 3.1, the next section presents a monitoring study employing repeated Airborne EM surveys to investigate the hydrogeological evolution of a site. Related to the temperature effects, after exhaustive data and model analysis, the AEM system was found to lack sufficient shallow sensitivity to detect temperature changes across the surveys, which were also conducted in closely similar seasonal conditions. Therefore, no temperature correction was deemed necessary. Nevertheless, this study strongly underscores the importance of conducting temporal studies using a time-lapse modeling approach, supported by on-field purposeful repeated data acquisitions.

Beyond the standalone developments presented in the next paper, this work—through the development of the time-lapse AEM modelling scheme—provides an additional tool for planning AEM campaigns involving the acquisition of multitemporal datasets. These datasets can now be effectively modelled and interpreted, introducing a new dimension of information.

2.1.4 PAPER - TIME-LAPSE AIRBORNE EM FOR MONITORING THE EVOLUTION OF A SALTWATER AQUIFER – THE BOOKPURNONG CASE STUDY

Signora A.¹, Munday T.², Vonk M.A.^{3,4}, Fiandaca G.¹

¹*The EEM Team for Hydro & Exploration, Department of Earth Sciences, University of Milan (Italy). E-mail: alessandro.signora@unimi.it*

²*The Commonwealth Scientific and Industrial Research Organization | CSIRO Mineral Resources*

³*Department of Water Management, Faculty of Civil Engineering and Geosciences, Delft University of Technology. Delft, South Holland, The Netherlands.*

⁴*Artesia B.V., Schoonhoven, South Holland, The Netherlands.*

*** The manuscript presented in this section is under submission to the Geophysical Journal International and is reported in its complete form. ***

2.1.4.1 SUMMARY

This work presents a novel time-lapse modelling scheme for Airborne Electromagnetics (AEM) monitoring datasets, applied to study the hydro-related evolution of the Bookpurnong floodplain in South Australia. Additionally, it introduces a new wide-ranging approach for this type of study, incorporating new processing, validation, and interpretation tools.

Time-Lapse studies are widespread in the literature but are not commonly applied to model EM data, particularly AEM data. This is likely due to the challenges of performing overlapping acquisitions with inductive systems. The key features of the new time-lapse scheme, which address these issues, include the definition of independent forward and model meshes, essential for considering unavoidable discrepancies in multitemporal AEM acquisition locations, and the incorporation of system flight height into the inversion. This proved crucial for achieving satisfactory data fitting and limiting artifact propagation in the time-lapse models. Additionally, a novel dedicated processing workflow for AEM monitoring is presented. This has proven important for effectively processing the multitemporal dataset, which presents new

challenges in identifying noise coupling arising from the use of different systems across surveys, possible variations in acquisition settings operated by different field crews, and eventual changes in the survey area over time.

The results of the time-lapse geophysical models are evaluated with an Independent Hydrogeological Validation (IHV), designed to support the geophysical results validation and interpretation phases with hydrogeological assessment of the system.

At Bookpurnong, along a sector of the Murray River floodplain, multitemporal AEM survey were collected in 2015, 2022 and 2024, to study the groundwater system evolution over time. The time-lapse models show significantly smaller variations compared to the independent ones, while delineating sharply bounded variation zones across the floodplain. This demonstrates the effectiveness of the new time-lapse scheme in minimizing inversion artifacts typically encountered when comparing independent modelling results featured by differences in regularization, discretization, and with worsened equivalence issues.

The AEM models are first validated through comparison with resistivity borehole measurements, revealing a strong match between the two methodologies and spatial variations coherent with the meandering of the river across the floodplain. These variations are ultimately validated and interpreted using the IHV approach, which revealed a direct correlation between the hydrological stress of the Murray River and the response of the shallow aquifers. Additionally, time-lapse geophysical models, combined with a hydrostratigraphic analysis, allow for the establishment of a direct correlation between shallow and deep hydrogeological responses.

We believe that the time-lapse methodology developed in this work can be applied to AEM multitemporal studies, surpassing the results of single-time acquisitions by enabling the study of a wide range of natural process with great accuracy and at the basin scale.

Key words: *Airborne Electromagnetic, AEM, Time Lapse Inversion, Hydrogeophysics*

2.1.4.2 INTRODUCTION

Airborne ElectroMagnetic (AEM) surveys have seen growing application in recent years for environmental and hydrogeological studies (Viezzoli et al., 2009; Knight et al., 2018; Goebel et al., 2019; Chandra et al., 2019, 2021; Dumont et al., 2021; Minsley et al., 2021) demonstrating their ability to effectively characterize the subsurface electrical properties across extensive areas with ever-improving precision. An overview on AEM for geo-hydro applications is

provided for instance by Auken et al., (2017). AEM systems enable the collection of data over hundreds of line kilometres in a single day, with measurements typically taken every few tens of meters and interpretations reaching depths of several hundred meters. Furthermore, system accuracy and data repeatability are crucial in multitemporal geophysical analysis, where subsurface features must be consistently detected across temporal datasets with sufficient precision to capture target-signal anomalies over time. This is particularly true in hydrogeophysical studies at the basin scale, where accurately imaging geological heterogeneity and changes related to hydrogeological processes at the relevant scale is essential.

Geophysical temporal studies have evolved from traditional comparison of separate inversions to time-lapse frameworks: they aim to emphasize data-driven changes in the models while minimizing variations caused by noise, inversion artifacts, and limiting equivalences issues. Various time-lapse modelling procedures have been proposed in the literature, often employing specialized noise cancellation techniques. Examples include the ratio inversion (Daily et al., 1992), the cascaded inversion (Oldenborger et al., 2007; Miller et al., 2008), and the difference inversion (LaBrecque and Yang, 2001). More recently, time-lapse approaches have been developed to integrate two or more time steps into a simultaneous inversion, incorporating all datasets within a unified framework (e.g., Kim et al., 2009; Hayley et al., 2011; Karaoulis et al., 2011a, 2011b). Despite the considerable time since the introduction of time-lapse techniques, examples of their application in AEM studies remain scarce in the literature (e.g., Beamish and Mattsson, 2003).

Several practical factors have limited the application of AEM monitoring compared to, for instance, multitemporal galvanic studies. These include the high cost of AEM surveys and the challenges in repeating the acquisitions precisely matching EM sounding locations and flight heights. These challenges are compounded by the use of different EM systems and variations in their field operation settings.

Additionally, the limited availability of modelling codes capable of handling AEM time-lapse data has likely hindered the broader adoption of such approaches. This limited development of such tools likely stems from the inherent challenges of time-lapse AEM inversion, which demands algorithms with a level of accuracy high enough to detect subtle changes in the subsurface. While major variations can often be captured without time-lapse approaches, detecting small, yet meaningful, differences requires that only data-driven changes are

reflected in the results. Ultimately, the sensitivity to such subtle variations should be limited by the resolution of the AEM system itself and not by the modelling accuracy.

In this work we propose a novel simultaneous time-lapse inversion scheme tailored for AEM applications that is able to handle differences in the acquisition lines and the flight height, as well as the use of different acquisition systems. Together with the novel inversion approach, we present a dedicated processing workflow for AEM monitoring data, which ensure consistent processing of multitemporal datasets and avoid inversion artifacts due to coupling noise.

The novel inversion and processing schemes presented in this study are applied to an AEM monitoring dataset composed of three surveys (approximately 20 km² in extent each), conducted with different SkyTEM (Sorensen and Auken, 2004) systems, on the Bookpurnong floodplain, South Australia. The goal of this temporal study is to understand water quality exchanges over time between the highly saline aquifers and the Murray River as it meanders through its floodplain. This is reached not only by analysing the geophysical results, but also through an Independent Hydrogeological Validation (IHV). The IHV is a novel operational tool meant to bridge geophysics and hydrogeology and, in this study, to validate the time-lapse models in addition to the more traditional approach using borehole resistivity measurements. Within the IHV, the Murray River streamflow and water quality trends will be analysed, providing insights into their impact on the underlying hydrogeological system.

In the following, we present the modelling strategy for the geophysical data, followed by its application to the Bookpurnong time-lapse study. Before presenting and validating the results in term of site evolution analysis, a hydrostratigraphic description of the site is provided.

2.1.4.3 MODELLING STRATEGY

GEOPHYSICAL MODELLING

The time-lapse inversion of AEM data in this work is carried out within the EEMverter (Fiandaca et al., 2024), in a simultaneous process in which all different data sets are inverted at once, with a data space $\mathbf{d}$ defined as:

$$\mathbf{d} = [\mathbf{d}_1, \dots, \mathbf{d}_{N_{TL}}] \quad (52)$$

in which $\mathbf{d}_i$ represents the i -th data sets and N_{TL} represents the number of different time-lapse datasets.

For each dataset $\mathbf{d}_i$, a corresponding model vector $\mathbf{M}_i$ is defined, with the whole inversion model space defined as:

$$\mathbf{M} = [\mathbf{M}_1, \dots, \mathbf{M}_{N_{TL}}] \quad (53)$$

Each model $\mathbf{M}_i$ contains two types of inversion parameters, the resistivity and the flight height: the resistivity is defined on a regular mesh, while the flight height is defined sounding-by-sounding. The inclusion of the flight height in the inversion process can be of great help for obtaining acceptable misfit and/or models in the time-lapse inversion, particularly in low-resistivity environments. In such environments, a small error in the height estimation results in either shallow time-lapse artifacts and/or in worsening data fitting.

The regular mesh for the definition of resistivity is then linked to a forward mesh for forward/Jacobian computations, following the approach presented for instance in Christensen et al., (2017) for 1D EM computations Zhang et al., (2021), Engebretsen et al., (2022), Xiao et al., (2022a) for 3D EM computations. The link between inversion meshes (hereafter named model meshes) and forward meshes is obtained through an interpolation: the inversion parameters $\mathbf{M}$ (i.e., resistivity in this study) are defined in the model meshes and then interpolated to the forward meshes (with $\mathbf{m}$ indicating the interpolated parameters), for the computation of forward response and Jacobian. The interpolation is carried out with a simple linear operator as:

$$\mathbf{m}_i = \mathbf{A}_i \cdot \mathbf{M}_i \quad (54)$$

where the index i represents the time-lapse index of the data sequence and the matrix $\mathbf{A}$ contains the interpolation weights, computed with a first-order inverse distance approach. Figure 40 reports a sketch of model and forward meshes architecture just described for a time-lapse inversion with $N_{TL} = 3$.

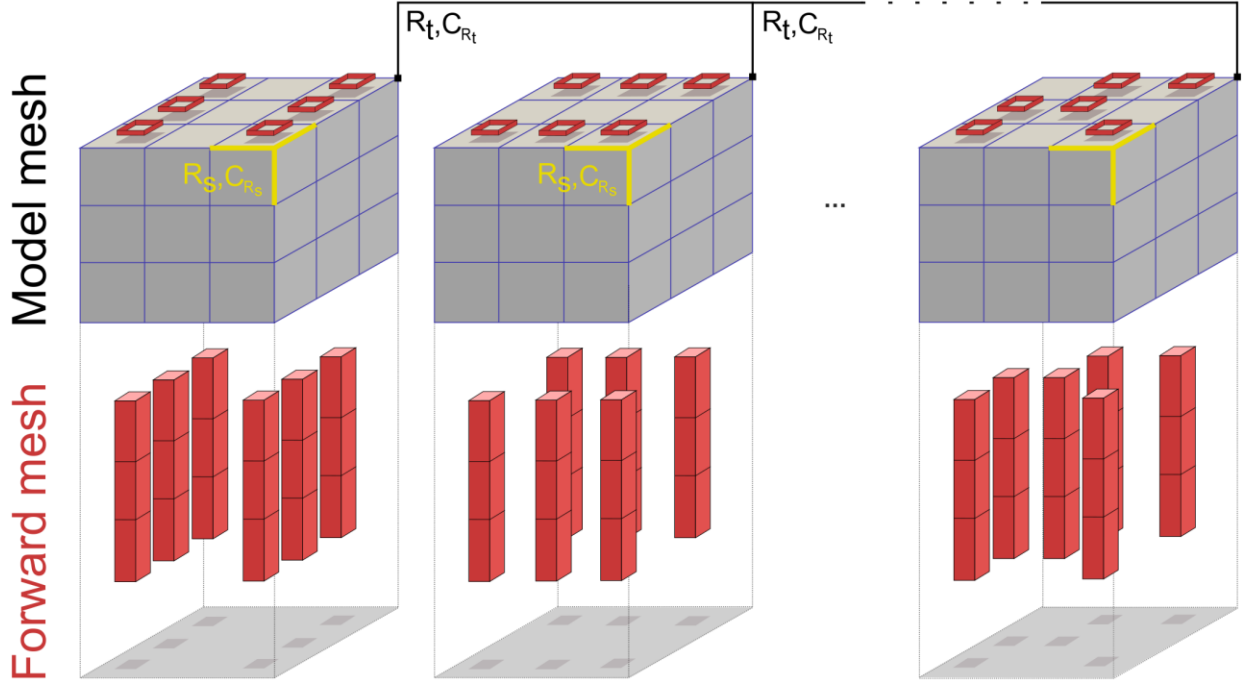


Figure 40 Model and forward mesh architecture for time-lapse modelling in EEMverter, where identical model meshes (grey meshes) for multitemporal modelling are defined and linked to data-specific forward meshes (red meshes) via interpolation. In this sketch, the forward meshes are the one typical 1D for AEM data, with soundings irregularly distributed across temporal surveys. On the model meshes two types of regularization are highlighted: vertical/horizontal intra-model constraints (yellow lines and text) and temporal model constraints (black lines and text).

The decoupling of model and forward meshes allows for a straightforward implementation of time-lapse inversion for surveys in which the data acquisition has non-coincident sounding positions, as it always happens in AEM applications: the model meshes for all temporal acquisitions can coincide in space, while the forward meshes follow the sounding positions. The inversion is carried out with an iterative re-weighted least-squares (IRLS) approach (Farquharson and Oldenburg, 1998) that minimizes the objective function defined as:

$$Q = \sqrt{\frac{(d - f(M))^T \cdot C_d^{-1} \cdot (d - f(M)) + M^T \cdot R_s^T \cdot C_{R_s}^{-1} \cdot R_s \cdot M + M^T \cdot R_t^T \cdot W^T \cdot C_{R_t}^{-1} \cdot W \cdot R_t \cdot M}{N_d + N_{R_s} + N_{R_t}}} \quad (55)$$

where C_d , C_{R_s} and C_{R_t} are the data and roughness covariance matrices (the subscripts s and t indicate space and time in the roughness regularization), the matrices R_s and R_t determine the

constrained parameters and $\mathbf{W}$ represents a re-weighting of the least-squares matrices for applying norms different from the L2.

The roughness matrices $\mathbf{R}_s$ and $\mathbf{R}_t$ are defined as:

$$\mathbf{R}_s = \begin{bmatrix} \mathbf{R}_{s_1} & \cdots & \mathbf{0} \\ \vdots & \ddots & \vdots \\ \mathbf{0} & \cdots & \mathbf{R}_{s_{N_{TL}}} \end{bmatrix} \quad (56)$$

$$\mathbf{R}_t = \begin{bmatrix} \mathbf{R}_{t_1+} & \mathbf{R}_{t_2-} & \cdots & \mathbf{0} & \mathbf{0} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{R}_{t_{N_{TL}-1}+} & \mathbf{R}_{t_{N_{TL}}-} \end{bmatrix} \quad (57)$$

In Eq. (56) the space-roughness matrix, indicated as $\mathbf{R}_s$, is a block-sparse matrix where each $\mathbf{R}_{s_i}$ matrix contains the vertical and horizontal constraints within model $\mathbf{M}_i$.

In Eq. (57) the space-roughness matrix $\mathbf{R}_t$ is composed by blocks that link each $\mathbf{M}_i$ to the next-in-time model $\mathbf{M}_{i+1}$ through $\mathbf{R}_{t_i+}$ and $\mathbf{R}_{t_{i+1}-}$ pairs (with +1 and -1 indicating the model differentiation).

Thanks to the de-coupling between model and forward meshes and the spatial correspondence of the resistivity model meshes, the constraint strength defined in C_{R_t} is uniform, regardless of the varying positions of the AEM soundings in the different datasets. In this work, the time-roughness is defined using the Asymmetric Generalized Minimum Support (AGMS) norm defined in Fiandaca et al. (2015), which minimizes the volumetric differences among constrained models.

The $n+1^{\text{th}}$ model update of the IRLS inversion procedure is computed as:

$$\begin{aligned} \mathbf{M}_{(n+1)} = & \\ \mathbf{M}_{(n)} + & \left[\mathbf{G}_{(n)}^T \cdot \mathbf{C}_d^{-1} \cdot \mathbf{G}_{(n)} + \mathbf{R}_s^T \cdot \mathbf{C}_{R_s}^{-1} \cdot \mathbf{R}_s + \mathbf{R}_t^T \cdot \mathbf{W}'_{(n)} \cdot \mathbf{C}_{R_t}^{-1} \cdot \mathbf{W}'_{(n)} \cdot \mathbf{R}_t + \lambda \mathbf{I} \right]^{-1} \\ & \cdot \left[\mathbf{G}_{(n)}^T \cdot \mathbf{C}_d^{-1} \cdot \left(\mathbf{d} - \mathbf{f}(\mathbf{M}_{(n)}) \right) - \mathbf{R}_s^T \cdot \mathbf{C}_{R_s}^{-1} \cdot \mathbf{R}_s \cdot \mathbf{M} - \mathbf{R}_t^T \cdot \mathbf{W}'_{(n)} \right. \\ & \left. \cdot \mathbf{C}_{R_t}^{-1} \cdot \mathbf{W}'_{(n)} \cdot \mathbf{R}_t \cdot \mathbf{M} \right] \end{aligned} \quad (58)$$

Where $\mathbf{G}_{(n)}$ represents the jacobian of the n^{th} iteration, which is a block-sparse matrix defined as:

$$\mathbf{G} = \begin{bmatrix} \mathbf{G}_{M_1} & \cdots & \mathbf{0} \\ \vdots & \ddots & \vdots \\ \mathbf{0} & \cdots & \mathbf{G}_{M_{N_{TL}}} \end{bmatrix} \quad (59)$$

in which $\mathbf{G}_{M_i}$ represents the jacobian of the i-th model and data sets. For computing the jacobian of the parameters defined on the model meshes $\mathbf{G}_{M_i}$, the jacobian computed in the forward meshes is propagated through the chain-rule of differentiation as:

$$\mathbf{G}_{M_i} = \mathbf{G}_{m_i} \cdot \mathbf{A}_i^T \quad (60)$$

Finally, the Depth of Investigation (DOI) in the inversion is carried put following Fiandaca et al. (2015).

SYNTHETIC EXAMPLE

The synthetic example in Figure 41 further highlights the importance of these time-lapse constrains. In this instance, the same type of AEM data later used in the field study is tested on a 100 m long synthetic model representative of the expected subsurface electrical properties at the at the real site. Specifically, SkyTEM data, with a 10-meter spacing between each EM sounding (red dots at the bottom of each model in Figure 41), are used to generate the forward responses over models that mimic the growth of a high resistivity anomaly ($50 \Omega \cdot \text{m}$) over a low resistivity half-space ($1 \Omega \cdot \text{m}$). In Figure 41, The black-box shape shown across the models represents the true high-resistivity anomaly evolution. The EM data includes gate times ranging approximately from $6\text{E-}06$ sec. to $12\text{E-}03$ sec. The modelling, as described in the previous section, is carried out using a 1D EM forward response and decoupled forward and model meshes, to ultimately compare the results obtained using independent and time-lapse frameworks. Both approaches use identical intra-model discretization and regularization to ensure that differences are solely due to the enforcement of AGMS temporal constraints in the time-lapse inversion.

In this noise-free example, the independent (Figure 41a) and time-lapse (Figure 41b) inversions exhibit significantly different models, while having an equivalent misfit value (approximately 0.3 in all cases). As expected, the time-lapse inversion yields more compact results due to the suppression of equivalence-driven artifacts thanks to the temporal regularization.

The example of Figure 41 the data was noise-free to highlight the characteristics of the time-lapse inversion framework and to reduce potential noise-related bias in the comparison. However, when repeating the same inversion with added noise—3% gate uncertainty plus a time-dependent noise decreasing as $t^{-\frac{1}{2}}$ with level equal to $1 \frac{nV}{m^2}$ at 1 ms—the models obtained with the time-lapse framework remained very similar. In contrast, the independent models further localize artifacts due to the noise effects. In both cases, the data fitting was equivalent, with misfit values close to 1. The noise-added example is not shown here for brevity, but the performance of the time-lapse framework in suppressing non-data-driven differences under realistic noise conditions will be extensively presented in the field application sections.

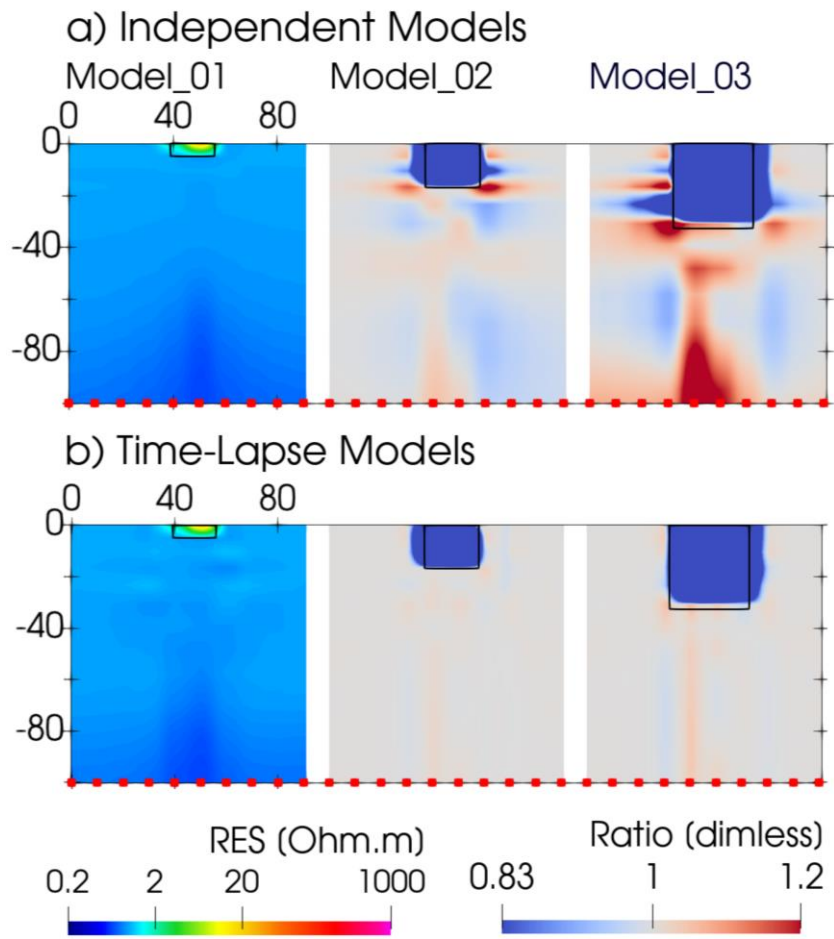


Figure 41: Synthetic test comparing Independent and time-lapse schemes for inverting AEM temporal series. (a) Independent inversion models. (b) Time-lapse inversion models. From left to right in both (a) and (b), the true models simulate the growth of a high-resistivity anomaly with its true shape delineated by the overlaying black line. The models are shown over their DOI and the EM sounding positions are indicated at the bottom of each model (red dots).

THE BOOKPURNONG CASE STUDY

The case study presented in this work is located on a stretch of land of approximately 20 km² in the Bookpurnong floodplain of the River Murray, South Australia. In this part of the Murray Basin, the river, groundwater system and agricultural areas are heavily managed to cope with the natural high-salinity of the shallow unconfined aquifer.

The river has multiple weirs and locks where water levels are controlled. The river-aquifer interaction naturally forces saline water exchange towards the river, challenging the floodplain freshwater recharge. This directly threatens the survival of floodplain vegetation that depends on freshwater and complicates the use of groundwater for agricultural activities. River discharge and flood events are the primary source of freshwater recharge on the alluvial plain, but its natural hydrological balance is heavily influenced by the anthropogenic activities on floodplain.

Numerous studies have focused on the Bookpurnong area using geophysical methods (Berens et al., 2004; Munday et al., 2005; Viezzoli et al., 2009; Hatch et al., 2010), also for supporting hydrogeological analysis. The following sections present the time-lapse modelling of AEM data repeatedly acquired over Bookpurnong (2015, 2022, 2024), aiming to describe the thickness, lateral extent, and evolution of the freshwater lens with the highest resolution. Both qualitative and quantitative analyses will be provided, with the evolutionary interpretation supported by geophysical validation through resistivity borehole measurements and through the Independent Hydrogeological Validation, offering an additional layer of integration between geophysics and hydrogeology.

HYDRO-GEOLOGICAL SETTING

HYDRO-STRATIGRAPHY

The Bookpurnong area lies within the Renmark Trough, a transitional zone where sedimentary sequences can reach thicknesses up to 500 meters. These Cainozoic sediments form a closed groundwater basin, with the Murray River serving as the only surface connection to the Southern Ocean through its mouth. This hydro-stratigraphical setting led to naturally high salinity in the aquifers, as rainfall, surface water, and groundwater accumulated within the basin over the past half a million years, combined with limited recharge capacity. For a comprehensive description, refer to Brown, (1989). The main regional lateral flow in the Bookpurnong area is from east to west, with highly saline groundwater significantly

contributing to salt discharge as it flows into the River Murray. The site topography is characterized by highland and floodplain areas. The highlands have elevations ranging from approximately 30 to 50 m.a.s.l., while the River Murray has carved a floodplain valley with ground elevations between 9 and 18 m.a.s.l.

An overview of the geological units is sketched in Figure 42 and listed below, including the maximum thickness and the salinity range of each formation, where available, as reported in Yan et al., (2005), which provides a more comprehensive description:

- Woorinen Formation (Unsaturated): Quaternary unconsolidated red-brown silty sand and clay (aeolian dune)
- Blanchetown Clay (Unsaturated): Quaternary lacustrine unit, locally silty/sandy. Found regionally within the unsaturated zone.
- Loxton sands (Unconfined to semiconfined aquifer): Highly heterogeneous coarse-grained sands transitioning into less permeable fine sands toward the base of the succession. These sands grade into low-permeability silty clay as they approach the Loxton Clay Formation (Max. Thickness: 38 meters; Salinity: 2–64 g/L).
- Coonambigdal Formation (Aquitard): Clay layer across the floodplain, consisting of clay and silt from episodic flooding (Max. Thickness: 11 meters)
- Loxton Clay and Bookpurnong Beds (Aquitard): Poorly consolidated plastic silts and shelly clays. (Max. Thickness: 25 meters)
- Monoman Formation (Unconfined to semi-confined aquifer): Clean, fine-to-coarse fluvial sands, deposited as point bar sands (Max. Thickness: 25 meters; Salinity: 13–46 g/L)
- Pata Formation (Unconfined to semi-confined aquifer): Poorly consolidated limestone with friable sand layers (Max. Thickness: 15 meters; Salinity: 8–32 g/L)
- Winnambool Formation (Aquitard): Grey to pale green calcareous marl and silty clay (Max. Thickness: 7 meters)
- Glenforlan Formation (Semi-confined aquifer): Grey sandy limestone, similar to Pata Formation (Max. Thickness: from 16–30 meters; Salinity: 3–27 g/L)
- Finniss Formation (Aquitard): Grey to dark grey clay with thin sand layers and hard bands (Max. Thickness: 14 meters)
- Mannum Formation (Confined aquifer): Well-compacted and cemented grey limestone. Upward leakage reported from the underlying Renmark Group aquifer (Max. Thickness: 101 meters; Salinity: 2–25 g/L).

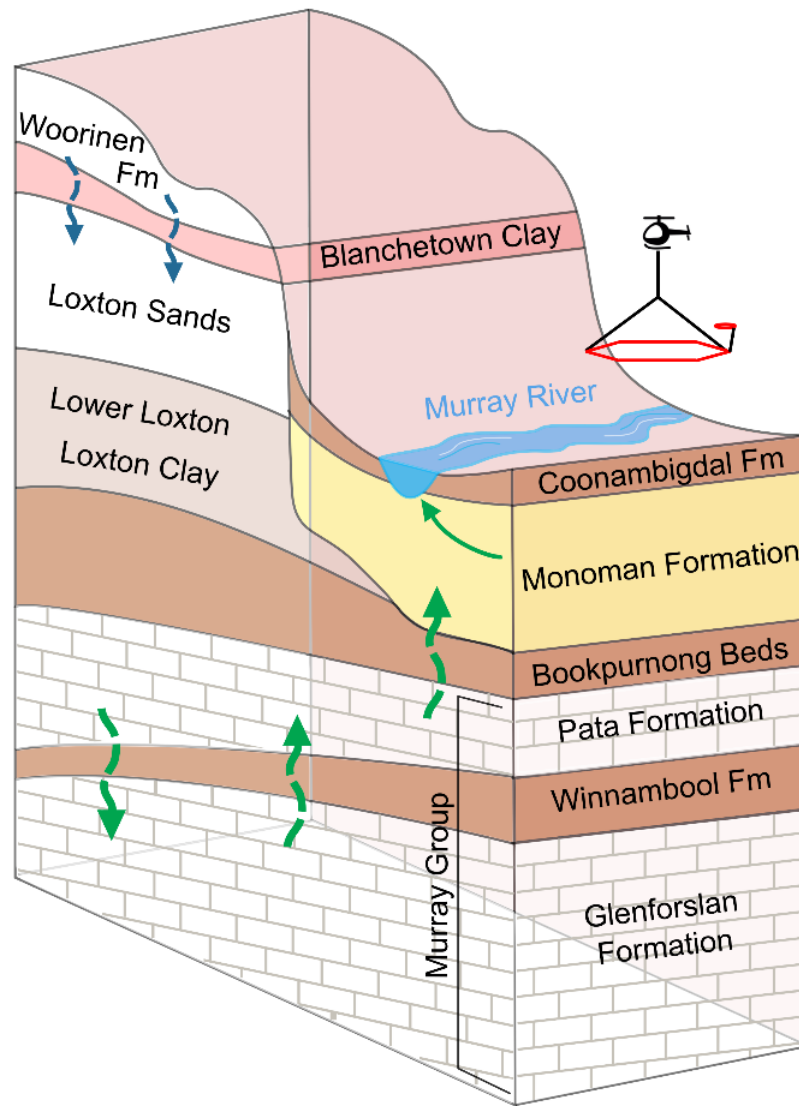


Figure 42: Sketch depicting the hydro-stratigraphic setting at the Bookpurnong site. The diagram is not to scale.

Yan et al., (2011) details the main horizontal flows within the hydro-stratigraphic units but reports also vertical flows between different aquifers due to incomplete isolation of the aquitards. Upward flows are reported to enable interaction between the Murray Group (Pata, Winnambool and Glenforslan Formations in Figure 42) and the watertable aquifer (Monoman Formation), particularly in areas where the lower Loxton Clay and Bookpurnong Beds have been eroded. Yan et al., (2011) also report intense salinity variations with depth. At the same time, the river is considered to impact the groundwater quality, with short-term fluctuations affecting the shallower Monoman Formation, while the Loxton Sands and the Murray Group respond to longer trends.

Based on the hydro-stratigraphy described above, the resistivity distribution on the floodplain expects high-resistivity anomalies ($>10 \Omega \cdot m$), corresponding to freshwater inputs from the Murray River, superimposed on a predominantly low-resistivity background ($<2 \Omega \cdot m$) representative of the high-salinity aquifers and clayey aquitards. Intermediate resistivity values are also expected in fresh-saltwater transition zones. In terms of temporal changes, increases in resistivity values across the floodplain will likely be indicative of freshwater migration on the floodplain, whereas decreases in resistivity are expected to indicate salinization dynamics. Additionally, given the reported vertical connectivity between aquifers and the variability of salinity with depth, also vertical resistivity changes, due to upward or downward water flows, may be observed. Resistivity in the highlands is expected to be relatively high, comparable to river freshwater values or higher. Limited river-induced variations are expected there. Still, changes may occur due to recharge processes and hydro-management activities.

WATER MANAGEMENT OF THE AREA

The river Murray is managed by several lock and weirs, with lock (and weir) 4 inside the case study area. At the locks, among others, the river water level, discharge and electrical conductivity are provided (SA Water, 2018). At the Bookpurnong site, the recharge of the shallow aquifer is also heavily influenced by the irrigation drainage in highland areas, significantly affecting salinity distribution in the floodplain. Agricultural freshwater drainage from the river and floodplain has increased the naturally occurring saline groundwater discharge into the river, prompting the construction of the Saltwater Interception Scheme (SIS) to mitigate this impact. In the Bookpurnong area, the SIS system, part of a larger-scale implementation across the hydrogeological district, is situated near the southeast meander of the river. Positioned on the highland bank, it extracts saltwater and diverts it into a disposal basin, favouring freshwater flow from the river into the saline lateral floodplain deposits.

GEOPHYSICAL SURVEY AND DATA PROCESSING

The geophysical dataset gathered in the Bookpurnong area consists of a multitemporal Airborne EM dataset measured in 2015, 2022, and 2024 (Figure 44a). Each survey overlaps the same flight lines, covering around 200 linear kilometres, with 30 acquisition lines of ~ 7 km each, spaced approximately 100 meters. The temporal acquisitions are designed to ensure data comparability between closely located measurements. Tie-lines were also measured to assess

data quality both at the time of acquisition and across different surveys. The May 2015 survey employs the SkyTEM³⁰⁴ system, which features a rigid transmitter framework (TX) with a 340.8 m² area and dual-moment energization with nominal peak currents of 9 A and 116 A featured by current turn-off ramp times of 3.5 and 50 μ s respectively (Figure 43, red lines). It is worth underscoring that no data can be retained before the transmitter current was fully shut down. The respective TX OFF-times are 1.018 ms and 10 ms, with acquisition frequencies of 275 Hz and 25 Hz, allowing the accurate retrieval of early and late times. The receiver (RX) is mounted in the so-called zero position, where the RX coil is positioned to minimize the primary field flux interference. The RX features a 105 m² area with a 210 kHz low-pass cut-off frequency filter for the Z component and a high-moment front gate time of 70 μ s. In June 2022, the AEM survey employs a SkyTEM³¹² FAST system to overlap the same lines. The dual-moment measurement strategy remains, using a rigid transmitter framework with an area of 342 m². The respective peak currents for the High Moment (HM) and Low Moment (LM) are 6 A and 110 A, with repetition frequencies of 275 Hz and 25 Hz, turn-off ramp times of 12 and 300 μ s and OFF-times of 1.018 ms and 15.0 ms (Figure 43, green lines). The receiver coil, placed in the zero-position, is featured with a 206.8 kHz low-pass cut-off frequency for the Z component and a front gate time of 370 μ s for the HM. In March 2024, the surveys were conducted using the SkyTEM³⁰⁴ system, which differs from the system used in 2015 for the TX area of 342 m², the HM current of 110 A, current turn-off ramp times of 5.5 μ s for the LM and 42 μ s for the HM, HM OFF time of 15 ms (Figure 43, blue lines), and a RX area of 325 m² with a cut-off frequency of 203 kHz for the Z component.

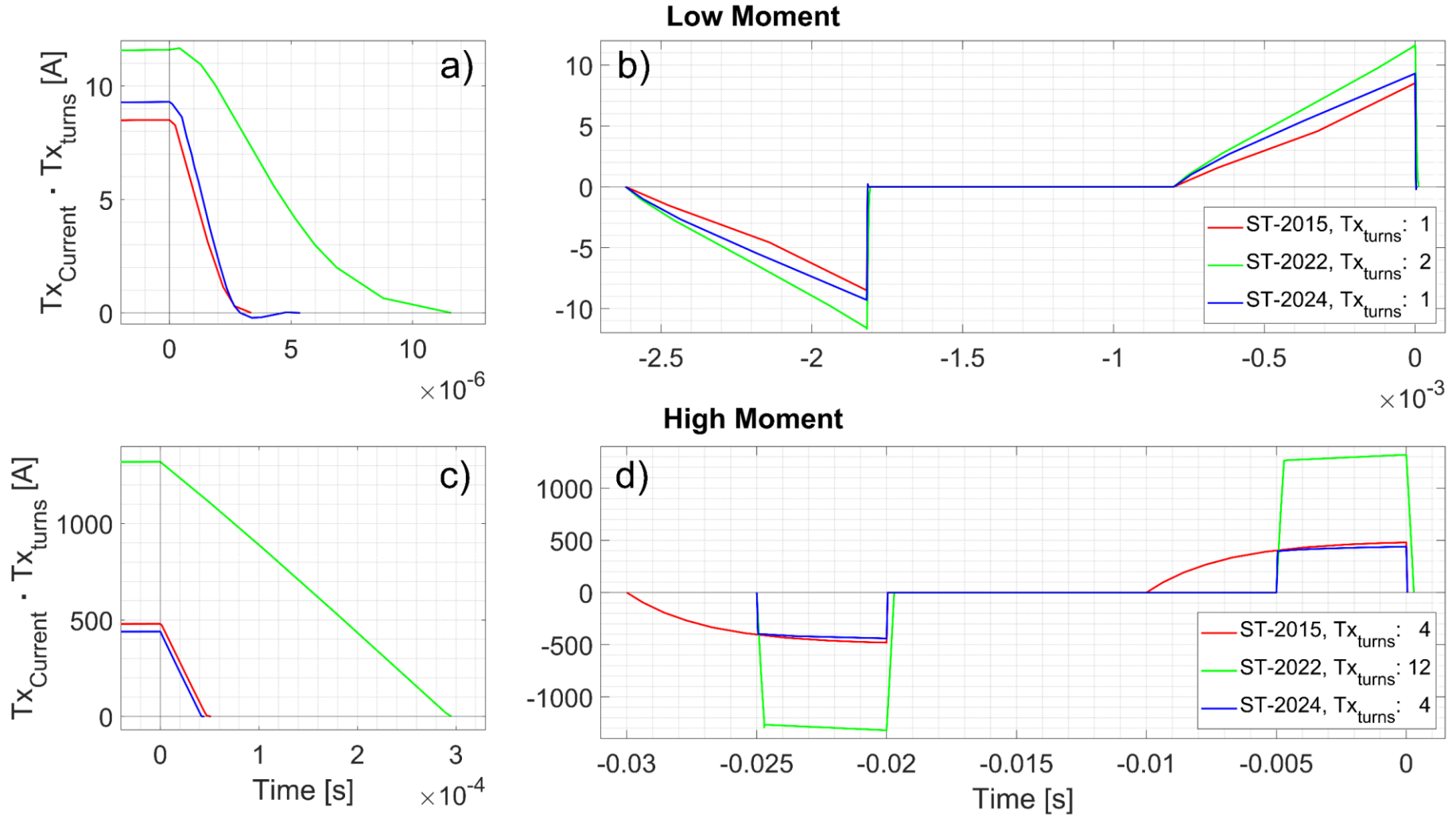


Figure 43: Energization characteristics of the SkyTEM systems used in the 2015 (red), 2022 (green), and 2024 (blue) Bookpurnong monitoring. The first row shows the low-moment energizations, highlighting the shut-down ramp (panel a) and a complete measuring cycle (panel b). The second row details the high-moment energizations.

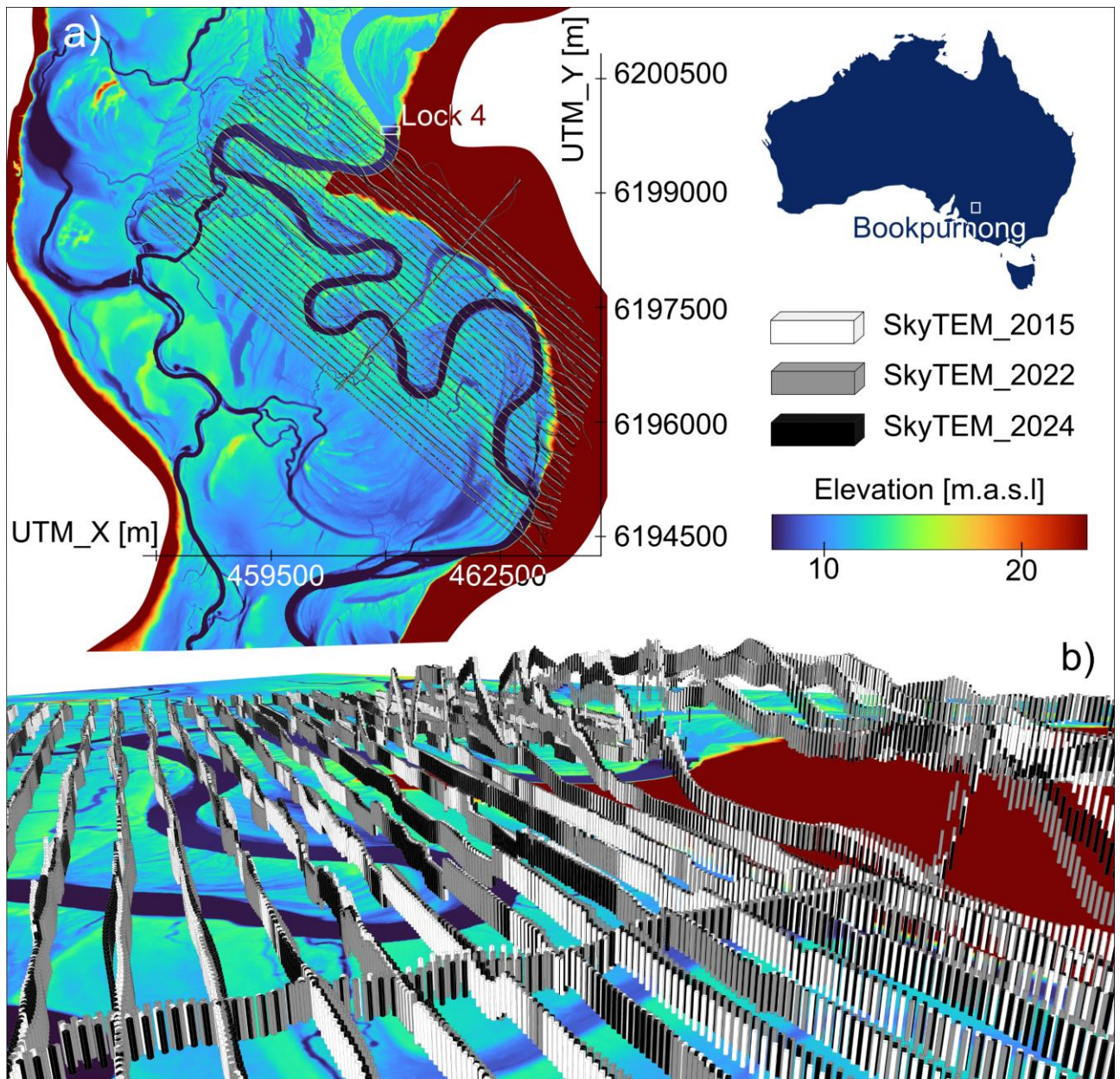


Figure 44: a) Elevation map of the Bookpurnong area overlaid by the AEM survey lines (2015, 2022, 2024) included in the time-lapse study. Lock 4 on the Murray River, a source of hydrogeological data for the next analysis, is also shown. b) Close-up view of the AEM soundings distributed across the floodplain, emphasizing the varying spatial positions of data points on temporal-overlapped survey lines.

The data processing is carried out accordingly to the recommendations presented in Viezzoli et al. (2013), with particular attention given to identify small power-lines that cross the Bookpurnong area, as well as other major noise sources such as roads and infrastructure. The processing is performed with a novel "simultaneous" approach, made possible by the flexible

handling capabilities of the EEMStudio (Sullivan et al., 2024). This approach is designed for processing temporal AEM series with overlapping flight lines, ensuring first that the same coupling-affected areas were removed across all datasets by defining the most conservative data-cleaning distance from the structure and applying it consistently. Furthermore, this workflow was necessary to assess noise content that appeared to vary temporally across different datasets. In fact, during the multitemporal datasets processing, noise disturbances near specific infrastructure were evident in one dataset but less pronounced in others. Such variations may result from factors such as system flight altitude, flight direction relative to the infrastructure, or differences in pre-processing made by the data provider.

An example of this is shown in Figure 45, where a small powerline disturbance is clearly visible in the SkyTEM 2015 (Figure 45c) and 2024 (Figure 45e) datasets, while SkyTEM 2022 dataset (Figure 45d) shows almost noise-free transients for the same location. Figure 45 provides just one example of the many similar cases identified during the Bookpurnong floodplain data processing, almost always linked to small power lines (Figure 45b) that cross the area. In most cases, we could rule out the possibility that these issues arose from newly constructed infrastructure, as the disturbances were absent in one of the later acquisitions, as shown in Figure 45, and that was also confirmed by examining historical maps (Google Earth LLC., LAT:-34.35°, LONG: 140.57° - WGS84). Moreover, in the instance of Figure 45, such noise-content differences were not ascribed to variations in systems ground height, as the systems were flown at approximately 40 meters above ground in all three surveys over this section. The coupling behaviour was also not attributed to the lateral distance from the power line. In fact, the most disturbed transients are from the 2024 dataset (blue dots), which are the farthest from the power line, while the least coupled data are from the 2022 dataset (green dots), which are closest to the power line location.

Questions remain open regarding the reasons behind these different effects recorded on the raw data. Nonetheless, this could have led to model artifacts if the datasets were processed separately without the “simultaneous” workflow, as it would have been difficult to identify the small power lines by analysing just one dataset at the time, as in the case of SkyTEM 2022 of Figure 45. For conservative reasons, any time the data were measured near a coupling structure, both the LM and HM data were removed across all temporal datasets.

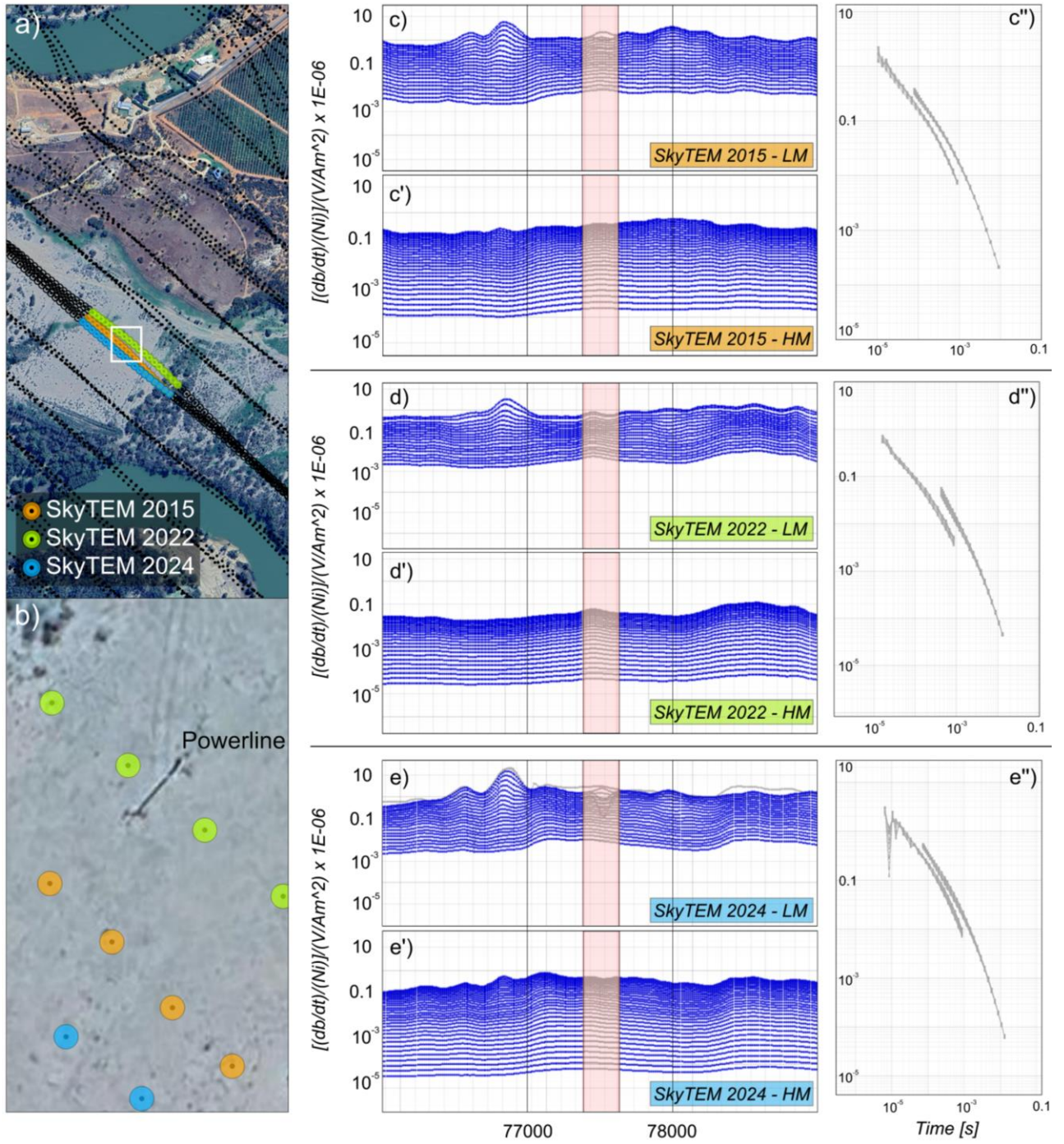


Figure 45: Different effects of the power line on the Bookpurnong 2015, 2022, and 2024 datasets. a) Zoomed-out map. The coloured dots indicate the EM soundings removed, highlighted by the red boxes in the panels on the right. The white square indicates the location of the power line. b) Zoomed-in view of the power line on the floodplain. c, c', c'') SkyTEM 2015 data for Low and High moments, with EM transients removed from the selection highlighted by the light red box. d, d', d'') Similar to the previous description, but for the SkyTEM 2022 data. e, e', e'') Similar to the previous description, but for the SkyTEM 2024 data.

DATA MODELLING AND GEOPHYSICAL VALIDATION

The data modelling follows the workflow outlined in Section 2.1.4.3, employing a 1-D EM forward response, which was shown by Viezzoli et al. (2010) to be an adequate approximation for depicting the geological features of this site. After the data processing, a total of 13868, 15734, and 14741 EM soundings were included in a first independent inversion round of the 2015, 2022, and 2024 datasets, respectively. The same data are subsequently unified within the time-lapse inversion framework. The purpose of running the independent inversions first is to establish a reference for tuning the time-lapse inversion and enable comparison between the two approaches on a real data application, allowing to move beyond the synthetic example.

Independent and time-lapse inversions were configured with some shared characteristics. Both follow a multicycle process (Fiandaca et al., 2024), starting with a preliminary cycle designed to run a single-layer inversion to set better starting values than homogeneous or gradient. This step preceded the subsequent multilayered cycle, where the model discretization consisted of 21 layers logarithmically spaced from 5 to 500 meters. This discretization was found to strike a good balance between system resolution, investigation targets, and the computational cost of the time-lapse inversion.

The regularization remained consistent between the independent and time-lapse models, and employed an L2 norm and vertical and horizontal constraints which allow model variations of up to 200% and 30%, respectively. Data uncertainties were incorporated through the inverse of the covariance matrix included in Eq. (55), accounting for them in the model updates. Regarding the model space parameterization, the AEM system flight height was included as an inversion parameter for both the independent and time-lapse inversions. This addition was crucial for achieving satisfactory misfit values in both approaches as the flight height has a significant impact on the computation of AEM responses, especially when operating in conductive environments.

As presented in Section 2.1.4.3, the time-lapse approach defines the forward and model meshes independently to account for the varying locations of EM soundings across different datasets. Time-lapse constraints are enforced between model meshes, using AGSM-type constraints (in this application: $\alpha = 1$, $p_1 = 1.35$, and $p_2 = 2.00$; Fiandaca et al., 2015).

Figure 46 reports the models obtained for the different years from both the independent and time-lapse inversion approaches. In the upper row, the independent models are presented: the 2015 model is displayed in terms of resistivity values (Figure 46a), followed by the ratio

between the 2022 and 2015 resistivity models (Figure 46b), and the ratio between the 2024 and 2022 resistivity models (Figure 46c). In the lower row, the corresponding time-lapse models (Figure 46d, 47e, and 47f) are shown. Here and in the following, all resistivity models are cropped over their DOI and when ratio models are computed, they are limited to the most conservative DOI among the two models involved in the ratio.

In the ratio panels of Figure 46, only variations greater than $\pm 5\%$ are displayed to isolate significant changes. Consistently with the results from the synthetic experiment (Figure 41), the time-lapse modelling reveals significantly more compact variations, resulting more conservative compared to the independent model space exploration.

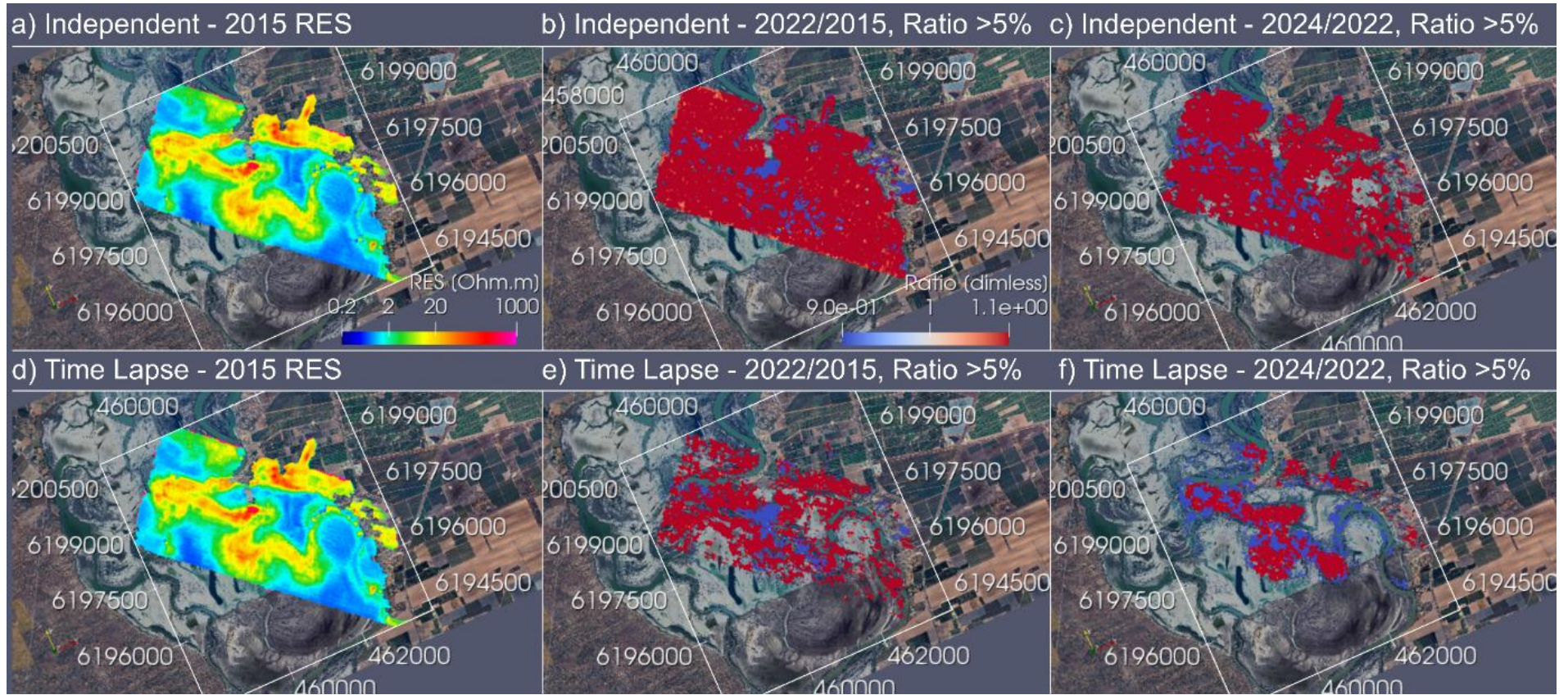


Figure 46: Real-case comparison of independent and time-lapse inversions performed on the Bookpurnong datasets. a) 2015 resistivity model obtained through independent inversion. b) Ratio of 2022 to 2015 independent resistivity models c) Ratio of 2024 to 2022 independent resistivity models. d) 2015 resistivity model obtained through time-lapse inversion. e) Ratio of 2022 to 2015 time-lapse resistivity models. f) Ratio of 2024 to 2022 time-lapse resistivity models. All ratio model shows differences greater than $\pm 5\%$.

MISFIT ANALYSIS

Regarding the misfit comparison between independent and time-lapse inversions, Table 11 presents the misfit values obtained for each model from both approaches, which are almost identical.

A uniform noise model was applied to the modelling of all three datasets, with the data gate standard deviations set to a minimum of 3%, summed with the standard deviation measured during the stacking procedure. For instance, Figure 47b shows the gate-by-gate standard deviation for all EM soundings acquired (prior to our processing) by SkyTEM in 2024. Thanks to the high signal-to-noise characteristics of the site, only the last few gates of the high moment display a slight increase in standard deviation.

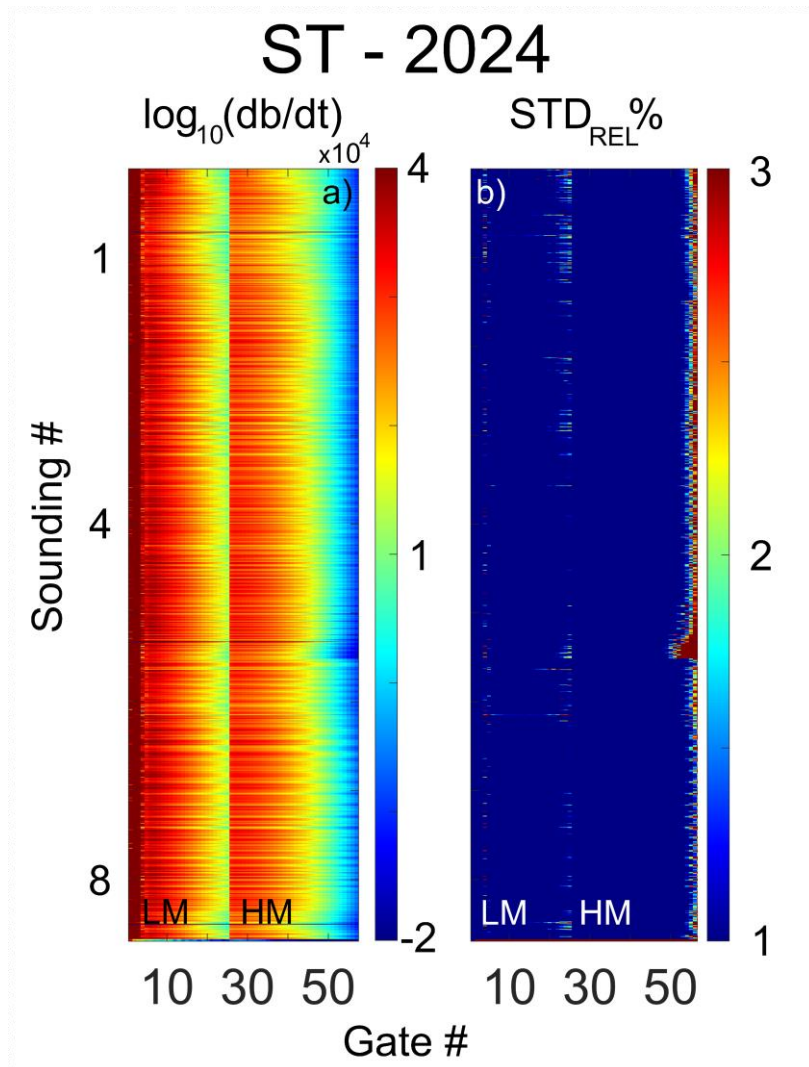


Figure 47: Data (panel a) and relative standard deviation (panel b) for all gates of the low and high moment of the EM soundings acquired during the SkyTEM 2024 survey. The reported data are prior to data processing.

The spatial distribution of the misfit is also alike between independent and time-lapse models. Figure 48 further illustrate the misfit distribution and the specific fitting of the decay curves. Figure 48a, 49d, and 49g display the "Gate-by-Gate" spatial distribution of the misfit, plotted according to the position of each EM sounding in the area for the 2015, 2022, and 2024 surveys, respectively. In this visualization, the misfit for each gate, defined as $\phi_{GATE,i} = \frac{|d_{GATE_{obs},i} - d_{GATE_{fwr},i}|}{\sigma_i}$, is plotted vertically, where the vertical position of each gate is given by $z_{GATE,i} = \frac{i}{N} \cdot z_{max}$. Here, i represent the index of the i -th gate, N is the total number of gates, and z_{max} is the maximum depth of the model. Since SkyTEM is a dual moment system, the first gate number for the High Moment correspond to $i_{First, HM} = N_{LM} + 1$, where N_{LM} is the total number of gates for the Low Moment data. This representation enables the identification of any spatial correlation in the misfit, and aids in visualizing systematic issues in the fitting of specific gates. This helps to pinpoint areas where certain gates might consistently exhibit poor fits, revealing potential inconsistencies or issues in the data also across the temporal datasets. Examples of this can be observed by examining the 2015 and 2022 misfit distributions across gates and space. In the 2015 dataset (Figure 48a), systematic issues are evident in the early Low Moment gates, as well as a poorly fitted band corresponding to the early High Moment gates. Additionally, the 2022 misfit distribution exhibits an interesting behaviour (Figure 48d), where the misfit for the first 2–3 low-moment gates increase sharply in the southern half of the survey compared to the same gate times in the northern part. These systematic misfits appear equivalent also in the independent inversions. There is no additional information available to explain these behaviours, though in 2022 case it could be due to an interruption between survey flights resulting in system changes. The 2024 survey appears to be uniformly well-fitted throughout (Figure 48g).

To the right of each Gate-by-Gate misfit plots, the data (blue lines) and fit (black lines) are shown for a survey line (Figure 48b, 49e, 49h) with individual transients extracted (Figure 48c, 49f, 49i) for further analysis. This transient visualization confirms the overall satisfactory data fitting.

Table 11: Data misfit values for the independent and time-lapse inversions of the Bookpurnong AEM surveys conducted in 2015, 2022, and 2024.

Data Misfit	SkyTEM ³⁰⁴ - 2015	SkyTEM ³¹² FAST - 2022	SkyTEM ³⁰⁴ - 2024
Independent inversions	1.22	0.78	0.80
Time-Lapse inversion	1.22	0.78	0.79

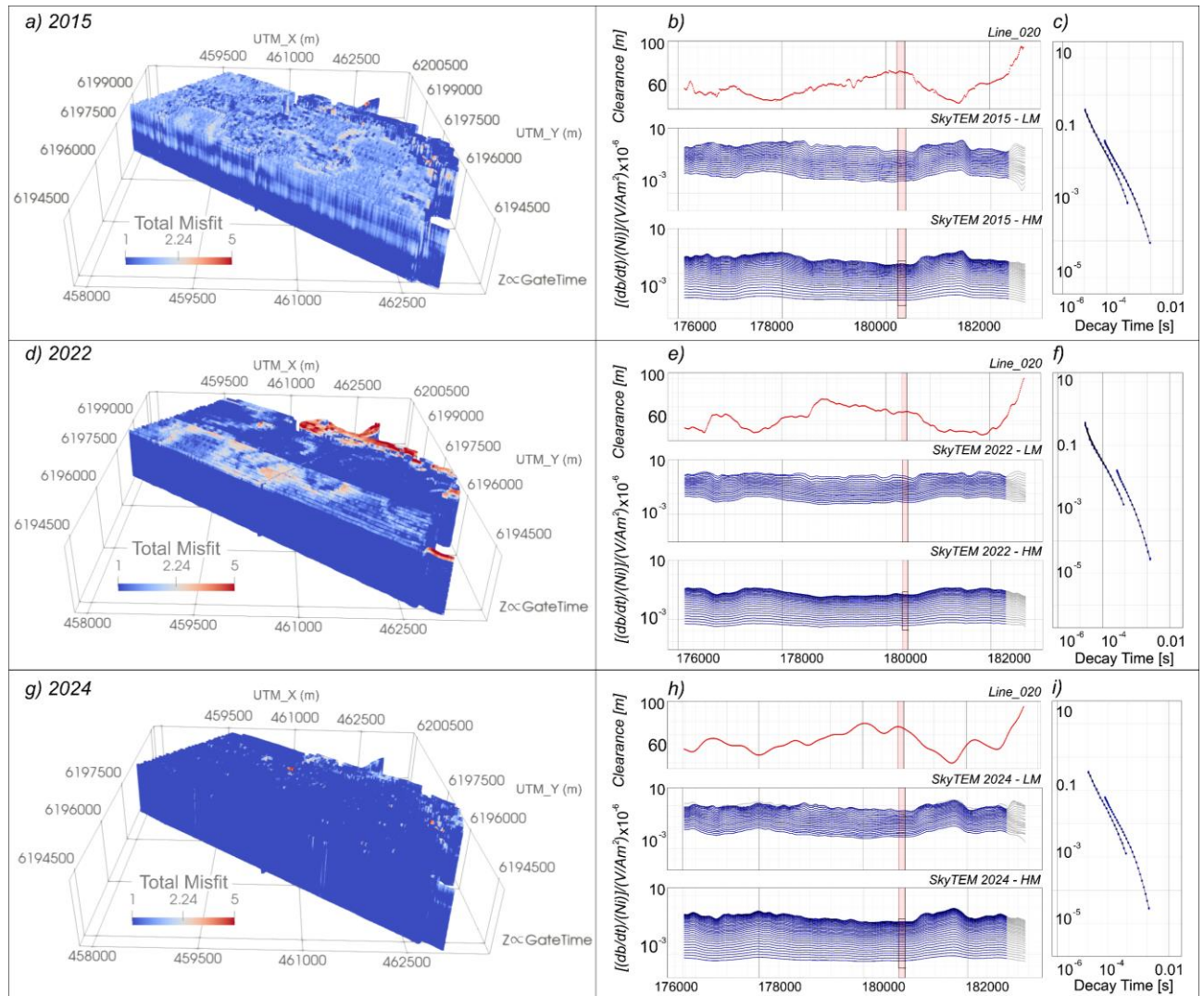


Figure 48: Spatial misfit analysis from the time-lapse inversion of the AEM series acquired over Bookpurnong. a-d-g) Gate-by-gate spatial distribution of the misfit for the 2015, 2022 and 2024 datasets, respectively (Z-axis is proportional to gate time). b-e-h) Comparison between data (blue line) and fit (black line) for the LM and HM components. The upper plots show system ground

clearance/height. c-f-i) Comparison between data (blue line) and fit (black line) for EM transients extracted from the area marked by a black box and red padding.

GROUND-TRUTHING

Before proceeding with the interpretation phase, the models are validated by complementing the misfit analysis with borehole resistivity measurements and geomorphological assessments. This analysis focuses on the 2022 time-lapse model as, in June of that year, two borehole log-EM measurements have been collected near the AEM survey line and close to a secondary channel of the Murray River (Figure 49). In Figure 49a, two AEM lines are extracted and the log-EM measurement locations highlighted. The sections are presented with a 10x vertical exaggeration, and the 3D interpolated model is overlaid with light transparency. This visualization highlights first how the high-resistivity features consistently align with the river channel and banks, demonstrating strong coherence between the model and the primary geomorphological features. Figure 49b allows the comparison between the closest AEM line to the log-EM borehole measurements, placed approximately 10 meters apart from the flight line. The match between the borehole log-EM data and the time-lapse model is precise, demonstrating the ability of the AEM model to accurately delineate the high-resistivity anomaly associated with the secondary channel of the Murray River. This is achieved despite the coarser vertical discretization compared to the log-EM sampling (~10 cm spacing). The blue mesh at the end of the section displays a portion of the AEM model mesh, with vertical discretization equal to that used for the 1D forward responses. Figure 49c and Figure 49d offer a more quantitative comparison, showing the 1D log-EM measurements (RMK_406 and RMK_407) are plotted alongside the five closest 1D AEM models. This comparison confirms the inversion ability to accurately capture the transition from high resistivity values near the river channel to lower resistivity at greater depths.

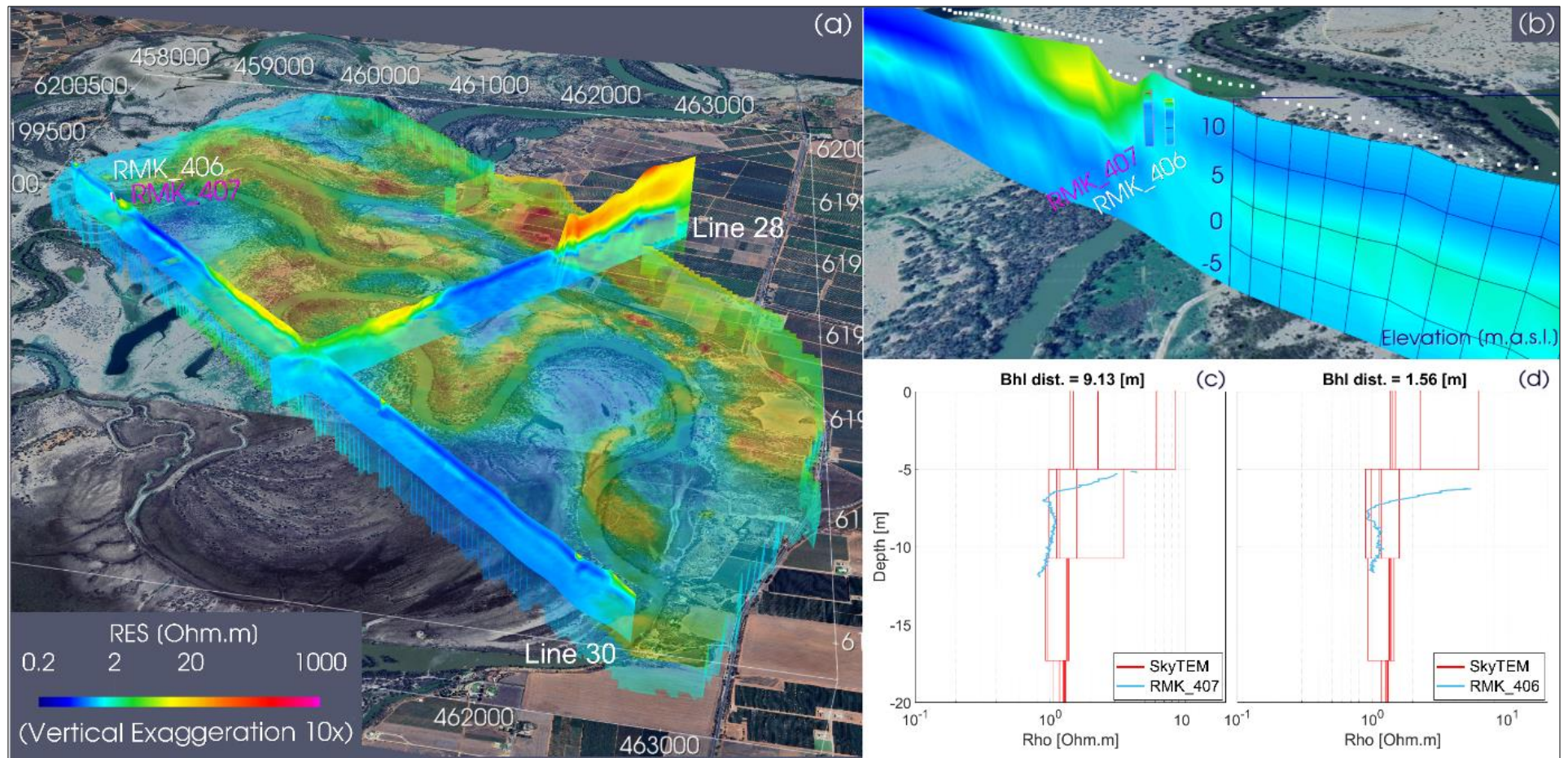


Figure 49: Comparison between the 2022 time-lapse AEM geophysical model and two log-EM measurements (RMK_406 and RMK_407), collected in June 2022. a) 2D sections for Line_28 and Line_30, showing the relative positions of the two log-EM measurements. b) Detailed view of Line_30 close to the borehole locations. The blue grid on the right represents the model mesh. Each white dot along the section indicates the position of an EM sounding. c-d) 1D comparison between the RMK_407 and RMK_406 log-EM measurements and the five closest 1D models extracted from the 2D line. The vertical scale is expressed as depth from the surface.

SITE EVOLUTION ANALYSIS

The evolution of the Bookpurnong area in terms of electrical resistivity is first analysed by displaying the ratios between the time-lapse geophysical models at different depths. Figure 50 presents horizontal sections at different elevations for the 2015 (panels a-h), 2022 (panels i-p), and 2024 (panels q-x) models. The 2015 model is used as the baseline and is reported in absolute resistivity values. For the 2022 and 2024 models, resistivity variations are presented as cell-by-cell ratios of the model mesh: the 2022 model is divided by the 2015 model, and the 2024 model by the 2022 model. This chronological models-division is meant to display the progressive temporal evolution of the site. In the ratio models, blue anomalies indicate a decrease in electrical resistivity compared to the previous time step, while red anomalies show an increase. The colorbar for the ratio models is displayed on a logarithmic scale where areas without significant changes appear in neutral white, while regions of increasing or decreasing resistivity intensify in colour, proportionally to the magnitude of temporal variation.

Overall, the ratio analysis shows that the major portion of the investigated volumes present no significant variations (white zones), with specific areas that present spatially-coherent differences. This not straightforward result, especially if considering that the time-lapse inversion is carried out on AEM datasets acquired using different systems, with non-coincident flight heights and acquisition lines. This finding demonstrates both the quality of the AEM time-lapse approach presented in this study, as well as the capability of the AEM method to be used in monitoring studies.

More in details, the results reveal that the 2022 survey displays an increase in resistivity in the shallow portions (Figure 50j and Figure 50k) from to 2015, especially at the elevation corresponding to the river channel. Deeper down a significant resistivity reduction follows near the model bottom (Figure 50o and Figure 50p). It is important to state the presence of a high-resistivity anomaly, located between -35 and -55 meters of depth, and clearly visible in the animation linked via the QR code of Figure 50 (see also Signora, 2025). This anomaly arises from the ratio between the 2022 and 2015 datasets, where the 2015 data exhibited a misfit issue in the early gates of the HM (see Figure 50a). Therefore, we consider this resistivity feature to result from this issue and deem it unlikely to be real. It will not be further analysed, as it is also outside the primary depth range of interest for the shallow river-aquifer interaction. However, should this depth range become of interest, a more detailed examination will be

necessary. An alternative perspective on this uncertain high-resistivity band is presented in Figure 51e.

In 2024, the evolution is nearly opposite to the 2022, showing a widespread decrease in shallow layers resistivity (Figure 50r and Figure 50s) and a strong resistivity increase below -70 meters, peaking at the model bottom (Figure 50o and Figure 50p). In this case, no resistivity anomalies are visible in the -35 to -55 meter depth range, further suggesting data issues in the 2015 dataset, as this time is not included in the ratio.

It is worth noting how the time-lapse models reveal opposite evolution in resistivity values between the shallow and deeper deposits. Nevertheless, the deep variations (Figure 50p and Figure 50x) among the years show a very similar spatial distribution, with well-defined boundaries corresponding to an area directly beneath the river channel.

To further assess the variations in electrical properties over the years, Figure 50 presents vertical slices extracted from a section oriented to intersect multiple times the alternation between the river channel meanders and the floodplain. In Figure 50a-c, the sections are displayed as resistivity values, while in Figure 50e-f, they are shown as ratios between models, consistently with the approach used in Figure 50. In Figure 51a-c, the areas with freshwater compatible values, indicated by the high-resistivity anomalies, are extending to a depth of approximately -20 meters in elevation. The vertical axis marks the -10 m elevation level, which roughly corresponds to the depth of the river channel. The ratio slices (Figure 51e and f) confirm the trends observed in Figure 50. In the 2022 model, there is an increase in resistivity in the shallow (down to -20 m.a.s.l.) and mid-depth sections (-35 to -55 m.a.s.l.), where the previously mentioned misfit issues occur. In contrast, the deeper sections show a decrease in resistivity. In 2024, a generalized decrease in resistivity is observed in the upper section, without significant changes at mid-depths, and an increase in resistivity at greater depths. For a more comprehensive evaluation, a video displaying slices across the entire floodplain is available via the QR codes provided in Figure 51 (Signora, 2025a, 2025b).

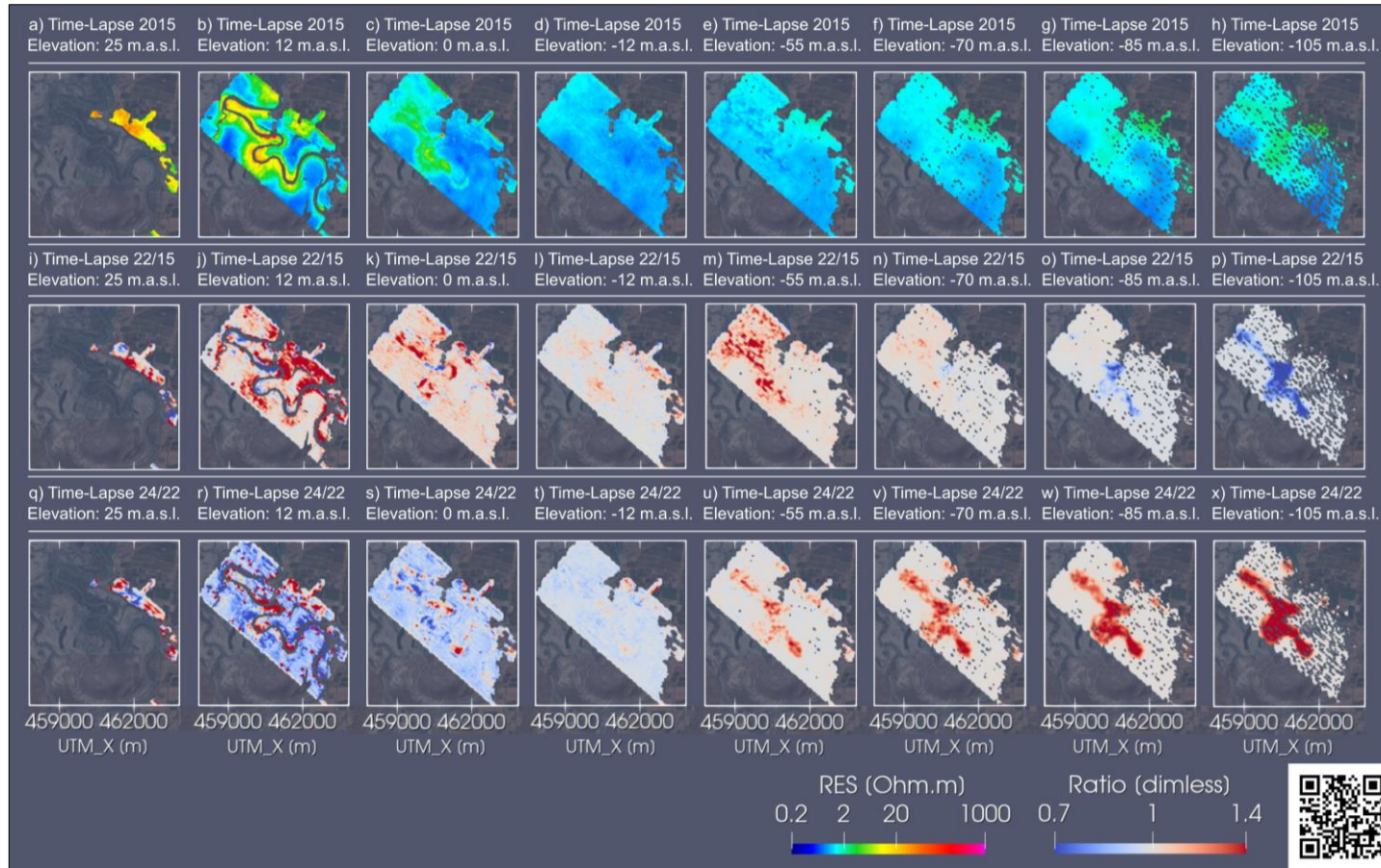


Figure 50: Depth slices from the time-lapse models obtained from the 2015, 2022, and 2024 AEM surveys. The elevation for each depth-slice is indicated in the top panel of each section. a-i) Resistivity depth-slices for the 2015 model. j-p) Corresponding depth-slices showing the cell-by-cell resistivity ratio between the 2022 and 2015 models. q-x) Depth-slices showing the ratio between the 2024 and 2022 models. In the ratio

depth-slices, areas with no significant change appear in neutral white. Scan the QR code to access the depth slices animation or visit <https://zenodo.org/records/14826900>.

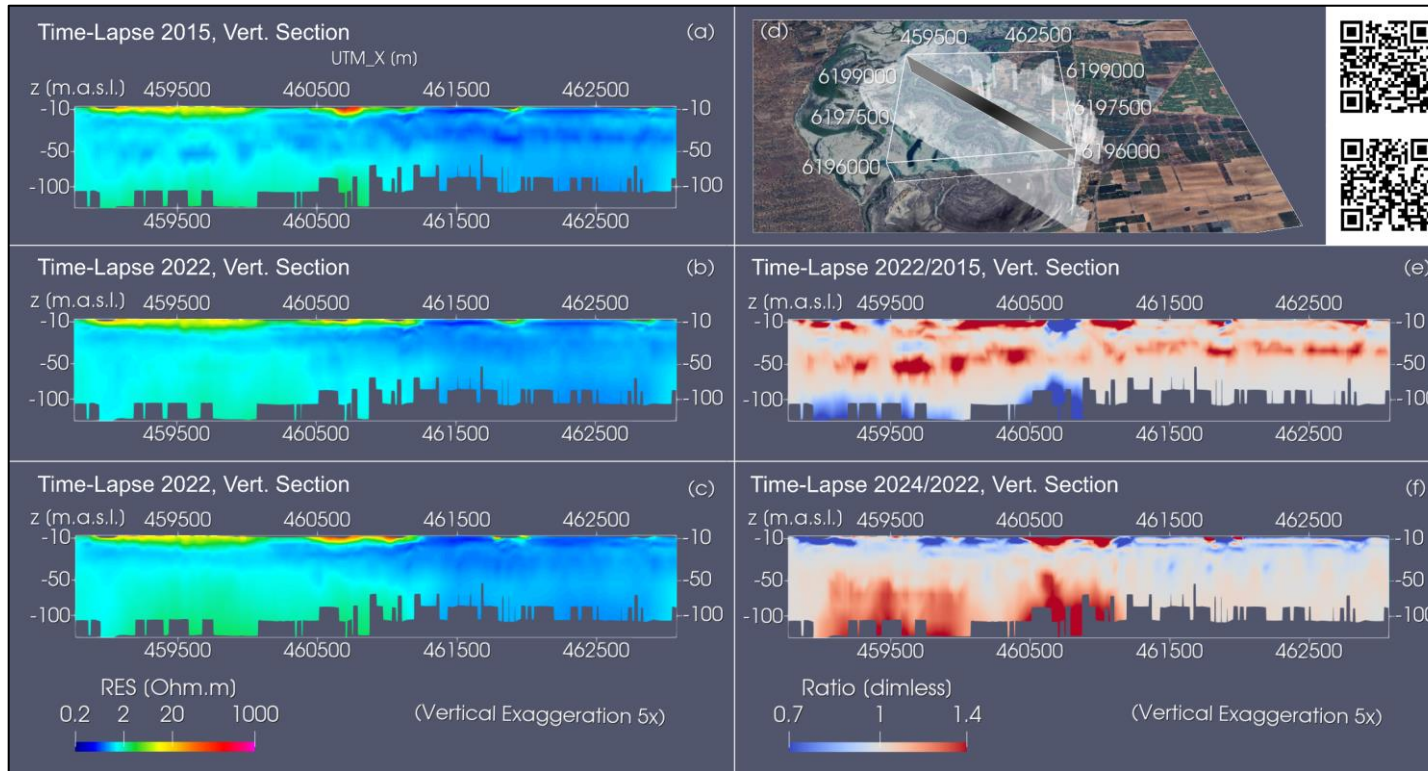


Figure 51: Vertical Slices from the time-lapse models obtained from the 2015, 2022 and 2024 AEM surveys. a-c) Resistivity vertical slices extracted at the location indicated in panel d. e) Vertical slice showing the cell-by-cell ratio between the 2022 and 2015 models. f) Vertical slice showing the cell-by-cell ratio between the 2024 and 2022 models. Scan the QR code to access the depth slices animations respectively for RES (top QR code or visit <https://zenodo.org/records/14826971>) and Ratio analysis (bottom QR code or visit <https://zenodo.org/records/14827081>).

INDEPENDENT HYDROGEOLOGICAL VALIDATION OF SHALLOW-MODEL EVOLUTION

The hydro-stratigraphy of the Bookpurnong area consists of alternating aquifers and aquicludes (Figure 42), with naturally occurring groundwater characterized by high salinity. Salinity levels vary both vertically between different aquifers and horizontally within the same hydrogeological structure. The Murray River serves as the primary source of freshwater, sustaining the shallow aquifer (Yan et al., 2005). The observed variations in the time-lapse geophysical models are therefore likely associated with changes in groundwater quality, driven by freshwater infiltration from the Murray River into lateral deposits.

This hypothesis can be tested using an Independent Hydrogeological Validation (IHV), a novel approach based on the available time-series data from the Murray River and designed to bridge geophysics and hydrogeology. Specifically, time-series of the discharge, water level and salinity of the Murray River are analysed where the water level and salinity data are measured at different locks on the river and flows calculated using site-specific rating tables (SA Water, 2018).

Figure 52 presents geophysical depth slices just below the river channel elevation, illustrating the resistivity distribution at 7 m.a.s.l. for the May 2015 model (Figure 52a), alongside ratio models for June 2022 and March 2024 (Figure 52b-c), all extracted at the same elevation. Figure 52d-f presents the River Murray time series for water level, salinity, and discharge, respectively, extracted from Lock 4 (see Figure 44) and Lock 7 (<https://riverdata.mdba.gov.au/map>). The overlying red lines indicate the AEM survey dates.

The comparison of geophysical depth slices with time series data begins on May 20, 2015 (Figure 52a), when river discharge was relatively low ($\sim 50 \text{ m}^3/\text{s}$). At this time, the AEM depth slice reveals high resistivity values concentrated near the river channel, suggesting freshwater infiltration into lateral deposits and highlighting the influence of river discharge on the hydrogeological system. By June 2022, when the first ratio depth slice is available, river discharge had significantly increased to $300\text{--}550 \text{ m}^3/\text{s}$, with water levels approximately 2.5 meters higher. This higher streamflow likely enhanced freshwater infiltration, as evidenced by a widespread increase in resistivity values (red areas in Figure 52b). This suggests an intensified exchange and dispersion of freshwater into the lateral deposits, driven by elevated river discharge. In May 2024, discharge levels had

decreased to $\sim 100 \text{ m}^3/\text{s}$, similar to those of 2015, while electrical conductivity (EC) had risen to $\sim 400 \text{ }\mu\text{S}/\text{cm}$, twice as high as in 2015 and 2022. This increase in EC coincides with a pronounced reduction in electrical resistivity in the geophysical slice (Figure 52c, blue areas), further indicating the dynamic interaction between river streamflow and infiltration of water into the surrounding deposits.

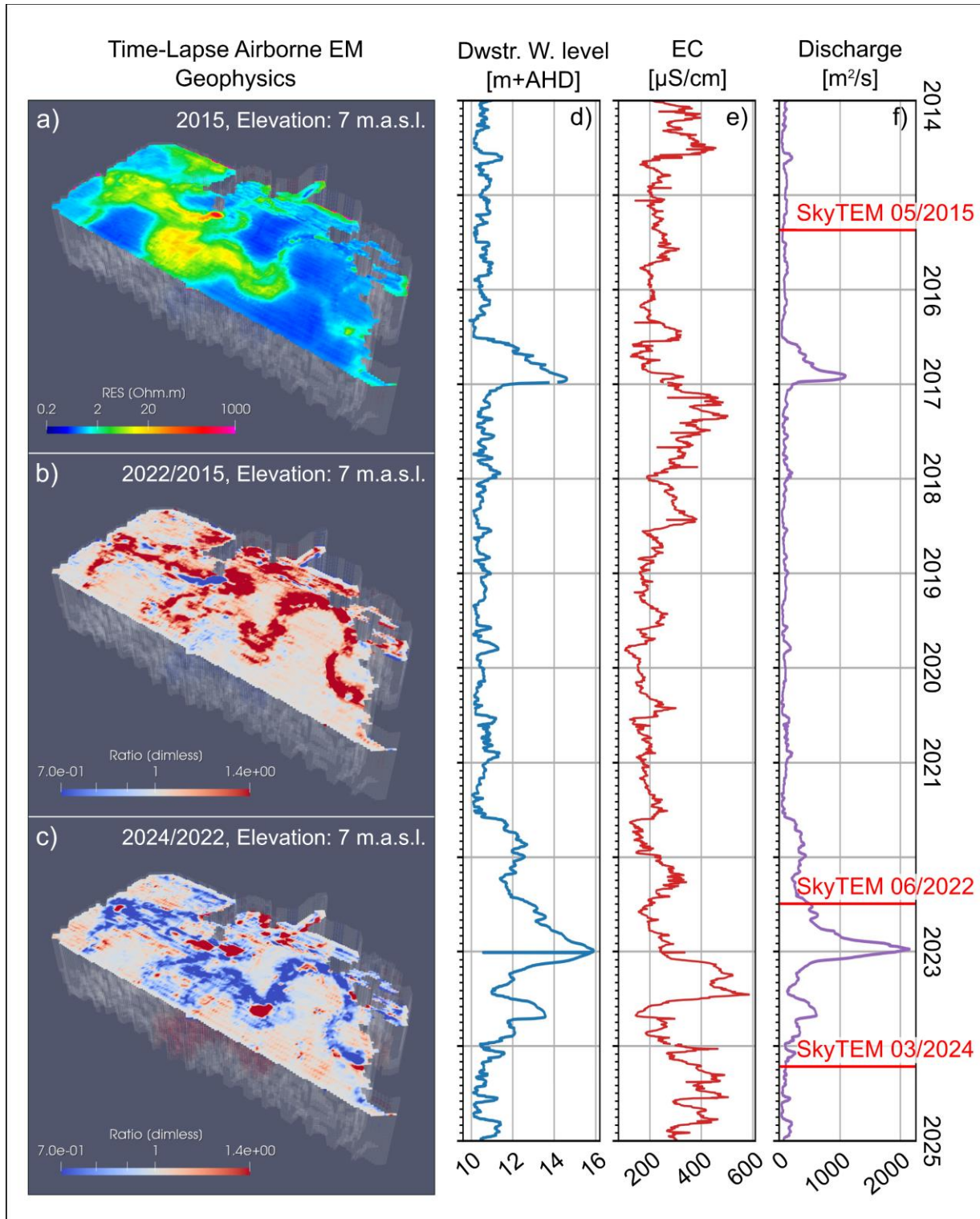


Figure 52: Comparison between the time-lapse AEM depth slices beneath the river channel elevation and the time-series hydrogeological indexes available for the site. a) Resistivity model from the 2015 time-lapse inversion. b) Ratio between the 2022 and 2015 time-lapse resistivity models. c) Ratio between the 2024 and 2022 time-lapse resistivity models. d) Water level series measured at lock 4 reported as meters AHD (Australian Height Datum). e) Water salinity series measured at lock 4. f) River Murray discharge as reported for lock 7 station.

Although the discharge values in 2015 and 2024 are similar, the total amount of freshwater infiltration is influenced not only by the streamflow at a given time but also by historical streamflow. To illustrate this, Figure 53 presents the resistivity ratio between the 2015 and 2024 models. Compared to the ratios shown in Figure 53, the variations in magnitude are less pronounced, and the resistivity changes exhibit a patchier distribution. Nonetheless, this figure confirms that the freshwater distribution in 2024 differs from that in 2015, despite the comparable streamflow rates. These observations support the hypothesis that, under similar streamflow conditions, the actual water balance is influenced by prior river discharge events. In the case of 2024, this includes the high discharge levels in 2023 and, notably, a major flood in December 2022. The large-scale flooding event likely contributed to the observed spatial variability and patchy resistivity patterns, highlighting the long-term impact of past hydrological conditions on groundwater dynamics.

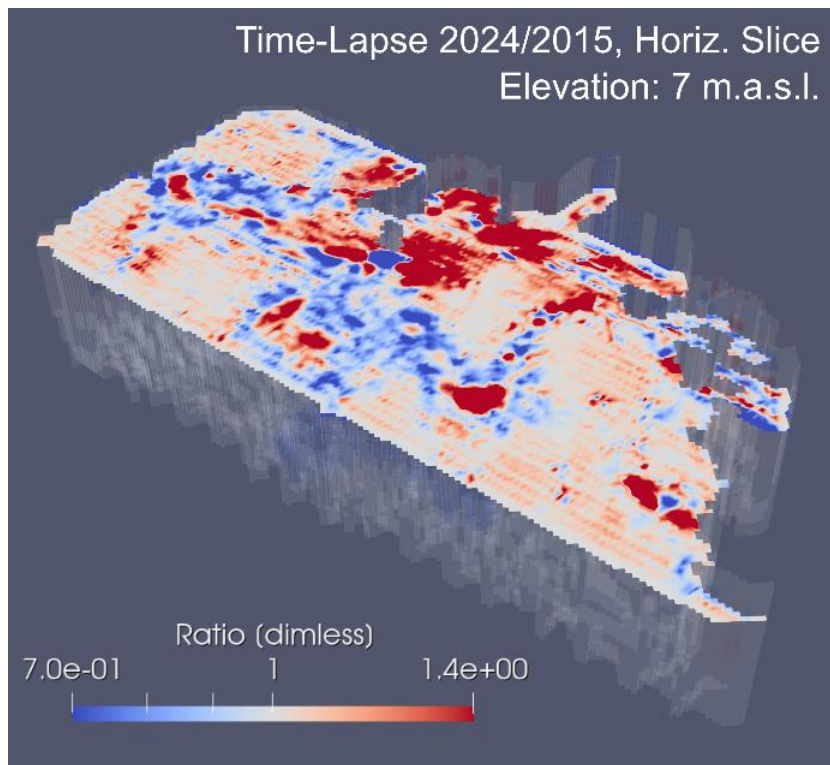


Figure 53: Ratio between the 2024 and 2015 time-lapse resistivity models

DEEP-MODEL EVOLUTION ANALYSIS

The IHV was intended to validate the changes observed in the shallow portion of the time-lapse geophysical models (elevation > -25 m.a.s.l.), supporting hydrogeological interpretations in the depth range of main focus for this study. This shallow section is particularly relevant for water management and the development of strategies to mitigate salinization.

The previous IHV does not extend to the deeper model analysis, whereas Figure 50 shows changes occurring throughout the entire depth of the models, including significant variations down to the depth of investigation at -105 m. Figure 54 offers a 3D view to highlight the spatial relationships between the changes in the ratio models (Figure 54d and 15e) and the absolute resistivity values distribution (Figure 54a-c). The resistivity volumes extracted in the latter frames aim to distinguish fresher water from the poorly resistive saline background ($< 1.5 \Omega \cdot \text{m}$). In the shallow region (> -25 m.a.s.l.), near the river channel, resistivity values above $2 \Omega \cdot \text{m}$ are extracted, while in the deeper parts (< -25 m.a.s.l.), values greater than $1.5 \Omega \cdot \text{m}$ are displayed. Table 12 provides a quantitative breakdown of the high-resistivity volumes, separating shallow and deep regions. Confidence intervals for the extracted resistivity volumes were calculated as percentage

variations by adjusting the lower and upper extraction limits by $\pm 0.1 \Omega \cdot m$. For the ratio models, the extraction limits were adjusted by $\pm 1\%$. Practically, for the shallow freshwater, the resistivity threshold was modified to 1.9 and 2.1 $\Omega \cdot m$, and the mean percentage variation was calculated relative to the volume extracted at the 2 $\Omega \cdot m$. The same procedure is applied to the deep fresh water volumes, this time varying the 1.5 $\Omega \cdot m$ threshold. Consistently, for the ratio models the 8% threshold was varied to 7% and 9%, and the mean percentage variation calculated. The volume analysis reveals that:

- i) The largest high-resistivity shallow volume occurs in 2022, consistently with the freshwater discharge analysis (IHV, Figure 52).
- ii) The smallest shallow high-resistivity volume is in 2024, with values similar to 2015, also aligning with the IHV.
- iii) In the deep region, the behaviour is opposite: the peak in high-resistivity volume is in 2024, with the lowest in 2022.

These deep variations are spatially evident in Figure 54a-c, and in the plan-view reported in the bottom-left corner of each panel. The volume ratios of Figure 54d and Figure 54e reinforce the previous statements, confirming that when shallow resistivity increases (now interpreted with the IHV as freshwater incomes), deep resistivity volumes decrease. Conversely, an increase in deep high-resistivity volumes is observed with a concurrent shallow resistivity decrease (reduced river discharge and freshwater), as seen in 2024.

Table 12: Shallow and deep volume variations for the 2015, 2022, and 2024 resistivity models (2nd to 4th column). Volumes variations for the volume ratios 2022/2015 and 2024/2022 (5th and 6th columns). For shallow volumes, extraction is based on resistivity values greater than 2 $\Omega\cdot m$ or differences exceeding $\pm 8\%$. For deep volumes, the resistivity threshold is reduced to 1.5 $\Omega\cdot m$. Green-shaded cells highlight the year with the highest freshwater-like resistivity volumes in both shallow and deep model portions, while red/blue-shaded cells indicate the greatest/smallest resistivity increase recorded in different years, either in shallow or deep sections.

	RES			RATIO	
	2015	2022	2024	2022/2015	2024/2022
	Volumes with $\rho > 2 \text{ Ohm.m [m}^3\text{]}$			Volumes with variations $> 8\%[\text{m}^3]$	
Shallow ($>-25\text{m.a.s.l.}$)	$3.68\text{e}07 \pm 6\%$	$4.21\text{e}07 \pm 4\%$	$3.59\text{e}07 \pm 4\%$	$1.01\text{e}07 \pm 9\%$	$3.06\text{e}06 \pm 7\%$
Deep ($<-25\text{m.a.s.l.}$)	Volumes with $\rho > 1.5 \text{ Ohm.m [m}^3\text{]}$			Volumes with variations $> 8\%[\text{m}^3]$	
	$8.8\text{e}07 \pm 60\%$	$1.7\text{e}08 \pm 70\%$	$1.98\text{e}08 \pm 40\%$	$1.09\text{e}07 \pm 9\%$	$1.43\text{e}+08 \pm 4\%$

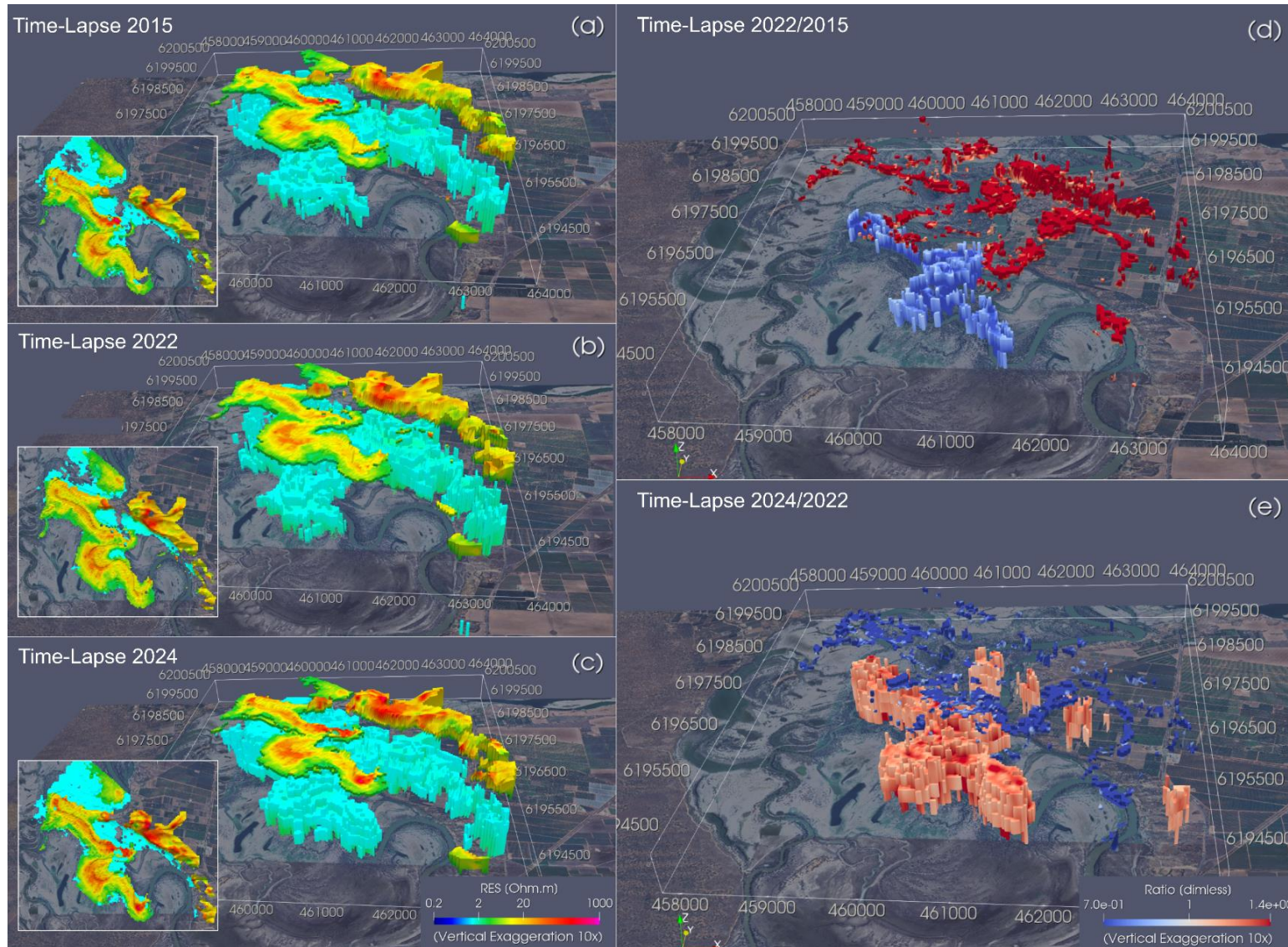


Figure 54: Resistivity volumes extracted for the shallow part (Elevation > -25 m.a.s.l, Resistivity > 2 Ohm.m) and the deep part (Elevation < -25 m.a.s.l, Resistivity > 1.5 $\Omega \cdot m$) from the 2015, 2022, and 2024 time-lapse models. The plan-view is shown in the bottom-left corner of each panel. d-e) Volumes showing differences greater than $\pm 8\%$ from the 2022/2015 and 2024/2022 ratio-models. Red colours indicate resistivity increases, and blue shows decreases.

The strong specular behaviour observed between the shallow and deep parts suggests a physical correlation, potentially indicating that shallow freshwater exchange influences the deeper, semi-confined aquifers. Interestingly, the analysis reveals the deep variations (<-50 m.a.s.l.) to concentrate beneath the river channel exchange area (see Figure 54). As a preliminary interpretation, the deep changes may be induced by freshwater inflows from the Murray River on the floodplain. This shallow-deep communication is coherent with Yan et al. (2011), which report vertical connectivity in the aquifers and decreasing salinity with depth in the hydrostratigraphic column. As freshwater accumulates in the shallow floodplain, a downward pressure gradient could be generated from the top of the hydro-stratigraphic column, caused by the fresh volume sitting on more saline water and preventing its sinking. Thus, the peak freshwater volume in 2022 (Figure 54d, shallow red anomaly) might have driven downward filtration, pushing more saline water downwards resulting in the observed low-resistivity anomaly (Figure 54d, deep blue anomaly). Conversely, in 2024, with reduced freshwater volumes, upward filtration could explain the increased deep resistivity anomaly (Figure 54e) due to fresher deep water rising. Although still preliminary, these deep variations align with the reported vertical interconnection of aquifers in the area, salinity trends, and the localization of deep variations within the projection of the river channel. This suggests a potential relationship between shallow and deep hydrogeological domains, providing valuable insights for land managers and hydrogeological modelers. To expand and validate these interpretations, a new Independent Hydrogeological Validation (IHV) should be planned as a future step, likely requiring more advanced hydrogeological modelling

2.1.4.4 CONCLUSIONS

In this work, a novel simultaneous time-lapse inversion scheme is proposed and applied to a multitemporal AEM dataset, proving able to handle differences in acquisition lines, flight heights, and the use of different acquisition systems. Specifically, to address discrepancies in acquisition lines—an unavoidable aspect in AEM surveys—the time-lapse inversion scheme defines independently forward and model meshes, overcoming the modelling issue of non-coincident AEM soundings. Another modelling novelty is the inclusion of AEM system flight height in the inversion parameterization, which proved important throughout the study for achieving satisfactory data fitting and limiting artifact

propagation in the models—two issues that are particularly impactful in low-resistivity environments.

Along with this novel inversion approach, a dedicated processing workflow for AEM monitoring data has been defined to ensure effective processing of multitemporal datasets. This was deemed necessary since, during the study, these datasets revealed new challenges compared to traditional approaches, requiring a new data treatment method to prevent inversion artifacts due to coupling noise.

The field application focused on the Bookpurnong area, South Australia, along a floodplain sector of the Murray River, where multitemporal AEM surveys (2015, 2022, and 2024) were conducted to study the groundwater system and its evolution over time.

The time-lapse results showed small variations across most of the models, which is not a straightforward yet desirable outcome for time-lapse studies, considering that three different AEM systems, producing surveyed lines with discrepancies in location and flight height, were incorporated into the multitemporal modelling. These results, along with the localized sharply bounded variation zones over the floodplain, demonstrate the effectiveness of the applied time-lapse scheme. This achievement is also attributed to the new processing approach implemented prior to data modelling.

The time-lapse results were first assessed through misfit analysis, which showed an equal fit to the data compared to independent inversion while revealing significantly smaller variations in the models. The time-lapse model validation was then expanded by comparing borehole resistivity log EM measurements on the floodplain, revealing an accurate match between the two.

The time-lapse models showed resistivity variations that are highly coherent spatially with the meandering of the Murray River channel. The shallow variations were ultimately validated and interpreted using the Independent Hydrogeological Validation approach, revealing a direct correlation between the hydrological stress of the Murray River and the hydrogeological response of the floodplain aquifers. Regarding the deeper model variations observed, their specular response compared to the shallower variations led to the interpretation of a direct response-correlation between the of shallow and deep aquifers, that is coherent with the site hydrostratigraphic characteristics.

We believe that the time-lapse methodology developed in this work can be applied to AEM multitemporal studies for monitoring different processes, surpassing the results of single-

time AEM investigations and providing a new dimension for studying processes at the basin scale with great accuracy.

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REFERENCES

- Auken, E., Boesen, T., Christiansen, A.V., 2017. A Review of Airborne Electromagnetic Methods With Focus on Geotechnical and Hydrological Applications From 2007 to 2017, in: *Advances in Geophysics*. Elsevier, pp. 47–93. <https://doi.org/10.1016/bs.agph.2017.10.002>
- Auken, E., Christiansen, A.V., Kirkegaard, C., Fiandaca, G., Schamper, C., Behroozmand, A.A., Binley, A., Nielsen, E., Effersø, F., Christensen, N.B., Sørensen, K., Foged, N., Vignoli, G., 2014a. An overview of a highly versatile forward and stable inverse algorithm for airborne, ground-based and borehole electromagnetic and electric data. *Exploration Geophysics*, a 46, 223–235. <https://doi.org/10.1071/EG13097>
- Beamish, D., Mattsson, A., 2003. Time-Lapse Airborne EM Surveys Across a Municipal Landfill. *JEEG* 8, 157–165. <https://doi.org/10.4133/JEEG8.3.157>
- Berens, V., Hatch, M., Wilson, T., Hill, T., 2004. River-borne NanoTEM survey for location of salt accession to the River Murray at Loxton. *ASEG Extended Abstracts 2004*, 1–4. <https://doi.org/10.1071/ASEG2004ab010>
- Brown, C.M., 1989. Structural and stratigraphic framework of groundwater occurrence and surface discharge in the Murray Basin, southeastern Australia.
- Chandra, S., Auken, E., Maurya, P.K., Ahmed, S., Verma, S.K., 2019. Large Scale Mapping of Fractures and Groundwater Pathways in Crystalline Hardrock By AEM. *Sci Rep* 9, 398. <https://doi.org/10.1038/s41598-018-36153-1>

- Chandra, S., Tiwari, V.M., Vidyasagar, M., Raju, K.B., Choudhury, J., Lohithkumar, K., Nagaiah, E., Chandrapuri, S., Ahmed, S., Verma, S.K., 2021. Airborne Electromagnetic Signatures of an Ancient River in the Water-Stressed Ganga Plain, Prayagraj, India: A Potential Groundwater Repository. *Geophysical Research Letters* 48, e2021GL096100. <https://doi.org/10.1029/2021GL096100>
- Christensen, N.K., Ferre, T.P.A., Fiandaca, G., Christensen, S., 2017. Voxel inversion of airborne electromagnetic data for improved groundwater model construction and prediction accuracy. *Hydrol. Earth Syst. Sci.* 21, 1321–1337. <https://doi.org/10.5194/hess-21-1321-2017>
- De Paola, F., Giugni, M., Pugliese, F., Annis, A., Nardi, F., 2018. GEV Parameter Estimation and Stationary vs. Non-Stationary Analysis of Extreme Rainfall in African Test Cities. *Hydrology* 5, 28. <https://doi.org/10.3390/hydrology5020028>
- Dumont, M., Reninger, P.A., Aunay, B., Pryet, A., Jougnot, D., Join, J.L., Michon, L., Martelet, G., 2021. Hydrogeophysical Characterization in a Volcanic Context From Local to Regional Scales Combining Airborne Electromagnetism and Magnetism. *Geophysical Research Letters* 48, e2020GL092000. <https://doi.org/10.1029/2020GL092000>
- Engelbrechtsen, K.W., Zhang, B., Fiandaca, G., Madsen, L.M., Auken, E., Christiansen, A.V., 2022. Accelerated 2.5-D inversion of airborne transient electromagnetic data using reduced 3-D meshing. *Geophysical Journal International* 230, 643–653. <https://doi.org/10.1093/gji/ggac077>
- Farquharson, C.G., Oldenburg, D.W., 1998. Non-linear inversion using general measures of data misfit and model structure. *Geophysical Journal International* 134, 213–227. <https://doi.org/10.1046/j.1365-246x.1998.00555.x>
- Fiandaca, G., Chen, J., Zhang, B., 2024. EEMverter, a New Modelling Tool for Electric and Electromagnetic Data with Focus on Induced Polarization, in: NSG 2024 30th European Meeting of Environmental and Engineering Geophysics. Presented at the NSG 2024 30th European Meeting of Environmental and Engineering Geophysics, European Association of Geoscientists & Engineers, Helsinki, Finland, pp. 1–5. <https://doi.org/10.3997/2214-4609.202420166>

- Fiandaca, G., Christiansen, A.V., Auken, E., 2015. Depth of Investigation for Multi-parameters Inversions 2015, 1–5. <https://doi.org/10.3997/2214-4609.201413797>
- Fiandaca, Gianluca, Doetsch, J., Vignoli, G., Auken, E., 2015. Generalized focusing of time-lapse changes with applications to direct current and time-domain induced polarization inversions. *Geophysical Journal International* 203, 1101–1112. <https://doi.org/10.1093/gji/ggv350>
- Goebel, M., Knight, R., Halkjær, M., 2019. Mapping saltwater intrusion with an airborne electromagnetic method in the offshore coastal environment, Monterey Bay, California. *Journal of Hydrology: Regional Studies* 23, 100602. <https://doi.org/10.1016/j.ejrh.2019.100602>
- Hamilton-Smith, D.A., 2013. Salt mobilisation in a floodplain environment: using EM techniques to identify mechanisms that alter the distribution of saline groundwater.
- Hatch, M., Munday, T., Heinson, G., 2010. A comparative study of in-river geophysical techniques to define variations in riverbed salt load and aid managing river salinization. *GEOPHYSICS* 75, WA135–WA147. <https://doi.org/10.1190/1.3475706>
- Hayley, K., Pidlisecky, A., Bentley, L.R., 2011. Simultaneous time-lapse electrical resistivity inversion. *Journal of Applied Geophysics* 75, 401–411. <https://doi.org/10.1016/j.jappgeo.2011.06.035>
- He, Z., Hu, Z., Gao, Y., He, L., Meng, C., Yang, L., 2015. Field test of monitoring gas reservoir development using time-lapse continuous electromagnetic profile method. *GEOPHYSICS* 80, WA127–WA134. <https://doi.org/10.1190/geo2014-0195.1>
- Karaoulis, M., Revil, A., Werkema, D.D., Minsley, B.J., Woodruff, W.F., Kemna, A., 2011b. Time-lapse three-dimensional inversion of complex conductivity data using an active time constrained (ATC) approach: Time-lapse complex conductivity imaging. *Geophysical Journal International* 187, 237–251. <https://doi.org/10.1111/j.1365-246X.2011.05156.x>
- Karaoulis, M.C., Kim, J.-H., Tsourlos, P.I., 2011a. 4D active time constrained resistivity inversion. *Journal of Applied Geophysics* 73, 25–34. <https://doi.org/10.1016/j.jappgeo.2010.11.002>

Kim, J.-H., Yi, M.-J., Park, S.-G., Kim, J.G., 2009. 4-D inversion of DC resistivity monitoring data acquired over a dynamically changing earth model. *Journal of Applied Geophysics* 68, 522–532. <https://doi.org/10.1016/j.jappgeo.2009.03.002>

Knight, R., Smith, R., Asch, T., Abraham, J., Cannia, J., Viezzoli, A., Fogg, G., 2018. Mapping Aquifer Systems with Airborne Electromagnetics in the Central Valley of California. *Groundwater* 56, 893–908. <https://doi.org/10.1111/gwat.12656>

Minsley, B.J., Rigby, J.R., James, S.R., Burton, B.L., Knierim, K.J., Pace, M.D.M., Bedrosian, P.A., Kress, W.H., 2021. Airborne geophysical surveys of the lower Mississippi Valley demonstrate system-scale mapping of subsurface architecture. *Commun Earth Environ* 2, 131. <https://doi.org/10.1038/s43247-021-00200-z>

Modarres, R., 2007. Streamflow drought time series forecasting. *Stoch Environ Res Ris Assess* 21, 223–233. <https://doi.org/10.1007/s00477-006-0058-1>

Munday, T.J., Hill, A.J., Wilson, T., Hopkins, B., Telfer, A.L., White, G.J., Green, A., 2005. Combining geology and geophysics to develop a hydrogeologic framework for salt interception in the Loxton Sands aquifer, central Murray Basin, Australia. *Australasian Journal of Water Resources* 9, 163–168. <https://doi.org/10.1080/13241583.2005.11465274>

SA Water, 2018. River Murray Daily Flow data.

Sandersen, P.B.E., Kallesøe, A.J., Møller, I., Høyer, A.-S., Jørgensen, F., Pedersen, J.B., Christiansen, A.V., 2021. Utilizing the towed Transient ElectroMagnetic method (tTEM) for achieving unprecedented near-surface detail in geological mapping. *Engineering Geology* 288, 106125. <https://doi.org/10.1016/j.enggeo.2021.106125>

Signora, A., 2025a. Time Lapse Airborne EM for monitoring the evolution of a saltwater aquifer - The Bookpurnong case study. <https://doi.org/10.5281/zenodo.14826900>

Signora, A., 2025b. Time Lapse Airborne EM for monitoring the evolution of a saltwater aquifer - The Bookpurnong case study (video b). <https://doi.org/10.5281/zenodo.14826971>

Signora, A., 2025c. Time Lapse Airborne EM for monitoring the evolution of a saltwater aquifer - The Bookpurnong case study (video c). <https://doi.org/10.5281/zenodo.14827081>

Singh, V.P., 1998. Entropy-Based Parameter Estimation in Hydrology, Water Science and Technology Library. Springer Netherlands, Dordrecht. <https://doi.org/10.1007/978-94-017-1431-0>

Sorensen, K.I., Auken, E., 2004. SkyTEM—a New High-resolution Helicopter Transient Electromagnetic System. Exploration Geophysics 35, 194–202. <https://doi.org/10.1071/EG04194>

Sullivan, N.A.L., Viezzoli, A., Fiandaca, G., 2024. EEMstudio: Process and Model Electric and Electromagnetic Data with a QGIS Plugin 2024, 1–5. <https://doi.org/10.3997/2214-4609.202420154>

Telfer, A.L., Berens, V., Hatch, M., Palfreyman, C., 2005. Instream NanoTEM: providing increased resolution to stream salinisation and floodplain processes along the River Murray, southeast Australia. Australasian Journal of Water Resources 9, 155–161. <https://doi.org/10.1080/13241583.2005.11465273>

Tijdeman, E., Stahl, K., Tallaksen, L.M., 2020. Drought Characteristics Derived Based on the Standardized Streamflow Index: A Large Sample Comparison for Parametric and Nonparametric Methods. Water Resources Research 56, e2019WR026315. <https://doi.org/10.1029/2019WR026315>

Viezzoli, A., Auken, E., Munday, T., 2009a. Spatially constrained inversion for quasi 3D modelling of airborne electromagnetic data – an application for environmental assessment in the Lower Murray Region of South Australia. Exploration Geophysics 40, 173–183. <https://doi.org/10.1071/EG08027>

Viezzoli, A., Auken, E., Munday, T., 2009b. Spatially constrained inversion for quasi 3D modelling of airborne electromagnetic data – an application for environmental assessment in the Lower Murray Region of South Australia. Exploration Geophysics 40, 173–183. <https://doi.org/10.1071/EG08027>

- Viezzoli, A., Christiansen, A.V., Auken, E., Sørensen, K., 2008. Quasi-3D modeling of airborne TEM data by spatially constrained inversion. *GEOPHYSICS* 73, F105–F113. <https://doi.org/10.1190/1.2895521>
- Viezzoli, A., Jørgensen, F., Sørensen, C., 2013. Flawed Processing of Airborne EM Data Affecting Hydrogeological Interpretation. *Groundwater* 51, 191–202. <https://doi.org/10.1111/j.1745-6584.2012.00958.x>
- Viezzoli, A., Munday, T., Auken, E., Christiansen, A.V., Wilson, G.A., 2010. Accurate quasi 3D versus practical full 3D inversion of AEM data – the Bookpurnong case study. *Preview* 2010, 23–31. <https://doi.org/10.1071/PVv2010n149p23>
- Vonk, M.A., 2024. SPEI: A simple Python package to calculate and visualize drought indices. <https://doi.org/10.5281/zenodo.10816741>
- Xiao, L., Fiandaca, G., Maurya, P.K., Christiansen, A.V., Lévy, L., 2022a. Three-dimensional time-lapse inversion of transient electromagnetic data, with application at an Icelandic geothermal site. *Geophysical Journal International*, b 231, 584–596. <https://doi.org/10.1093/gji/ggac206>
- Xiao, L., Fiandaca, G., Zhang, B., Auken, E., Christiansen, A.V., 2022b. Fast 2.5D and 3D inversion of transient electromagnetic surveys using the octree-based finite-element method. *GEOPHYSICS*, a 87, E267–E277. <https://doi.org/10.1190/geo2021-0402.1>
- Yan, W., Howles, S., Howe, B., Hill, T., 2005. Loxton – Bookpurnong Numerical Groundwater Model 2005.
- Yan, W., Li, C., Woods, J., 2011. Loxton-Bookpurnong numerical groundwater model 2011. Volume 1, Report and figures. Science, Monitoring and Information Division, Department for Water, Adelaide.
- Zhang, B., Engebretsen, K.W., Fiandaca, G., Cai, H., Auken, E., 2021. 3D inversion of time-domain electromagnetic data using finite elements and a triple mesh formulation. *GEOPHYSICS* 86, E257–E267. <https://doi.org/10.1190/geo2020-0079.1>

3. INNOVATIVE APPROACH FOR E&EM REFERENCE AND CALIBRATION SITES

One of the objectives of this work is to propose improvements to the procedure for calibrating EM systems. This foundational step is meant to ensure that different EM instruments can produce measurements, and consequently models, that are quantitatively consistent with one another. In this study, the calibration focuses on Time-Domain AEM systems, where standard practices typically involve comparing measured signals with reference responses calculated from the best available subsurface model for the designated calibration site. Details on AEM systems calibration can be found in Section 1.1.2.2.

Building on the developments presented in the previous chapters, improvements to the calibration procedure will be proposed, starting with how the calibration model is defined and used to compute the reference signal. The first section of this chapter explores how the joint inversion approach (Section 1.2.1) can be leveraged to enhance the characterization of the subsurface electrical properties, surpassing the limitations of calibration sites based solely on EM data. This advanced capability of defining the subsurface model will be shown to be crucial for another aspect addressed in this work: accounting for the impact of temperature variations on EM systems data and their calibration.

3.1 EM CALIBRATION SITES AND SEASONAL TEMPERATURE EFFECTS

The current state of the art for establishing calibration sites for EM systems involves characterizing the designated site using ground EM measurements. These measurements are typically taken along a line where the AEM systems will also collect data. The AEM

measurements are then compared and adjusted against a reference response, calculated from the model derived from the ground measurements, which is regarded as the most accurate subsurface model available for the site (See section 1.1.2.2).

Despite the EM community does not advise a single, standardized procedure for performing this calibration, common practice recognize that the reference response needs to be calculated employing the complete description of the inductive system characteristics (e.g., Tx waveform, transmitter-receiver timing, receiver filter frequencies, front-gate times, etc.) to achieve precise calibrations avoiding significant inaccuracies in the computed forward responses (see Christiansen et al., 2011).

The first development we propose in the calibration procedure involves redefining how the reference model is established. Specifically, the approach involves defining the reference signal using a reference model derived from site characterization through the joint inversion procedure outlined in Section 1.2.1. The rationale for using a joint model to derive calibration models lies in its superior resolution compared to individual E&EM modelling, while consistently fitting the data.

Aside from providing the best possible subsoil model for calibration—and also avoiding the risk of an outdated calibration site being surpassed in resolution by the new system requiring calibration—it may seem, from a calibration point of view, that having a joint model does not make a significant difference if the system under calibration falls short of the resolution compared to the joint model. In such cases, the equivalence issue previously described would suggest that classic EM characterization of the calibration site might suffice for the calibration process.

However, this situation changes when the effect of temperature is considered in calibration procedures. As introduced in Sections 1.3.2 and 2.1.3, seasonal temperature variations can significantly impact EM data (Figure 37) and, consequently, EM system calibrations (Figure 38), suggesting that this factor can no longer be overlooked in these practices. More generally, EM system calibration must address any environmental factors that may change at the calibration site over time. This ensures that the calibration process adjusts the signal solely for differences arising from hardware variations and not from overlooked environmental changes, which would otherwise introduce inaccuracies into the calibration results. Then, a critical aspect is assessing the temperature effect along the calibration line, where different AEM systems, for instance, may undergo calibration at

different times of the year. The level of detail and accuracy in the available subsoil model plays a crucial role in effectively modelling this temperature effect. Consequently, whether the site model is derived solely from EM data or from a joint inversion approach (e.g., Figure 14b and c) makes a substantial difference in the accuracy of the thermal modelling that can be achieved.

To address this aspect, we start from Figure 55 to emphasize once again the impact of temperature on EM data across different subsoil models and EM systems. A comparison is proposed between thermal model variations (mimicking seasonal transitions from winter to summer) and inaccuracies in the receiver filter frequency. This aims to investigate the magnitude of the temperature effect on EM system calibration in comparison to a key component of the system transfer function, such as the filter value. Accordingly, Figure 55 shows the percentage differences between transients generated with variations in the filter cut-off frequency of $\pm 10\%$ (blue lines) and changes in the temperature model corresponding to three and six months (red lines). These results are presented for three different subsoil models: a homogeneous one, the model available for the more resistive Italian calibration site (Figure 10, panel e), and the model for the lower resistive Danish calibration site (as reported in Foged et al. 2013). The temperature modelling is conducted using real measured temperature data from the Italian and Danish locations, applying the same modelling procedure outlined in Section 2.1.2.3 for galvanic measurements and using a real field-measured temperature time series representative of the respective site. This procedure was adapted for EM forward computations, with a thermal diffusivity value set for the subsoil based on literature ranges, specifically $1.0 \times 10^{-7} \text{ m}^2/\text{s}$ (Dalla Santa et al., 2020). Figure 55 confirms, as previously observed in Figure 37, that the temperature effect is more pronounced in lower resistive sites and becomes increasingly evident with earlier gates, given their progressive sensitivity to shallower subsoil layers. Similarly, variations in the filter cut-off frequency have the most significant impact in low-resistive sites, with the strongest effect occurring when the correct filter value is underestimated compared to when it is overestimated. The black line serves as a control, where the signal is divided by itself, resulting in no variations. What stands out from this graph is that the magnitude of the temperature effect over six months (ΔT : Italian site 24°C , Danish site 18.3°C) almost always surpasses the impact of the filter effect across all subsoil models and systems. The temperature variations over three

months (ΔT : Italian site 12 °C, Danish site 8.8 °C) exhibits a smaller impact, as expected, yet still significant for EM systems calibration. In general, neglecting the temperature effect may have an even greater impact than inaccuracies in the system transfer function, particularly when considering low-resistivity sites and small-loop ground EM systems.

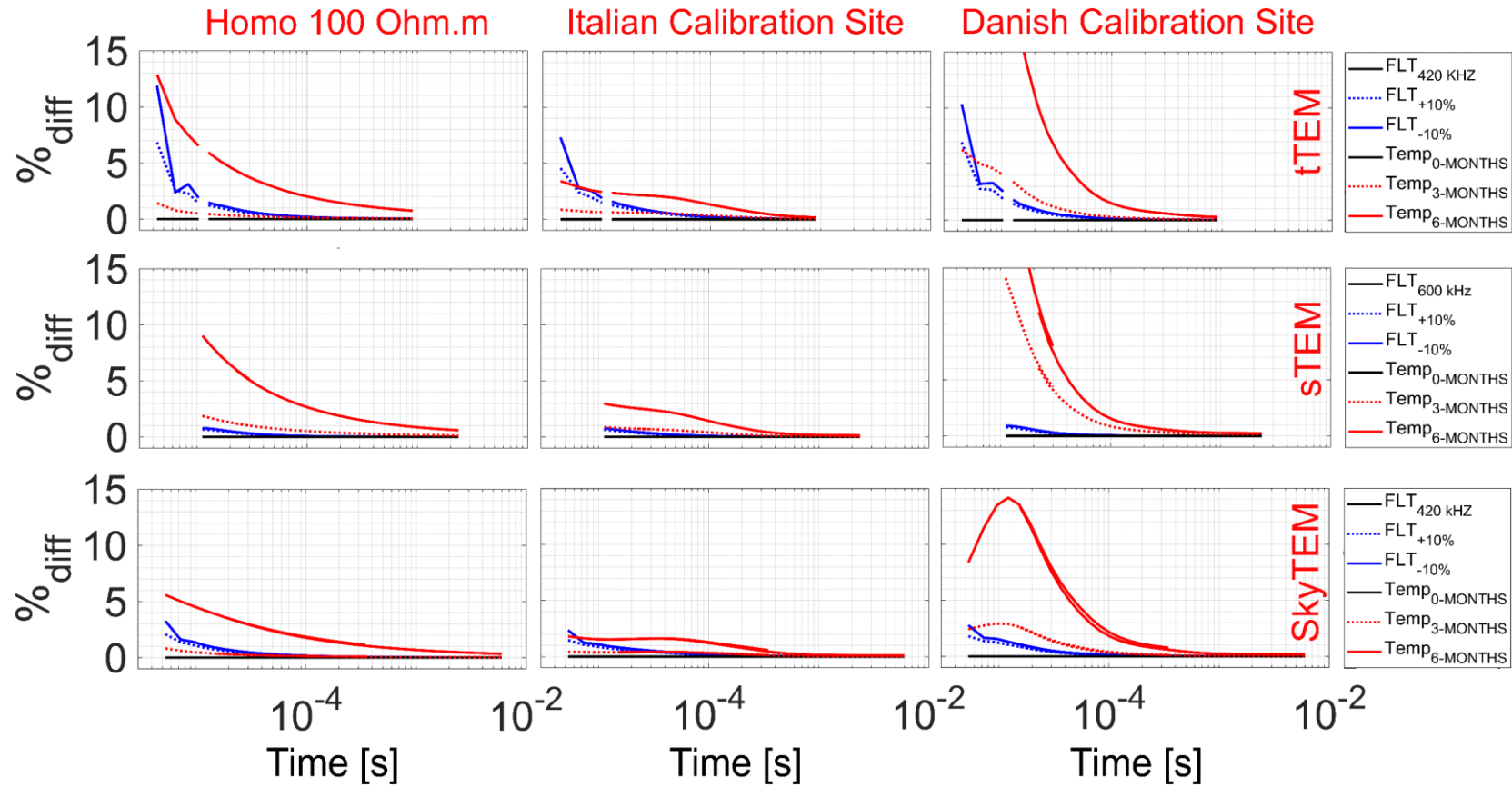


Figure 55: Comparison of temperature effects on subsoil electrical properties with filter inaccuracies in forward response computation for three EM systems across different subsoil models. Differences are shown as percentage variations from a base signal (black line), with temperature changes at 3 and 6 months (solid and dashed red lines) and receiver filter deviations of $\pm 10\%$ (solid and dashed blue lines). Results are presented for three EM instruments (top to bottom) and three subsoil models: a homogeneous 100 Ohm.m model (left), a high-resistivity model (Italian calibration sitem, center), and a low-resistivity model (Danish calibration site, right).

Accordingly, addressing the temperature effect whenever necessary during EM calibration procedures is considered crucial and this is where the definition of a calibration site through a joint model can provide key accuracy improvements. In fact, the precision in modelling the temperature effects affecting EM measurements at a specific site quantitatively depends on the precise definition of the electrical properties' distribution. To exemplify this, we focus on the characterization of the Italian calibration site (see Section 1.2.1.4) which features relatively resistive conditions. In Figure 56, a test where the independent EM and joint models available for this site, and previously shown in Figure 14, are used to model the temperature effects and producing the calibrations responses across six different months, from winter to summer conditions (Figure 56d).

Fig. Figure 56a-c shows the first 25 meters of the models from Figure 14, derived from the inclusion of only large-loop TEM data (a), small-loop data (b), and the galvanic data for the full joint modelling (c). These three models were then used to produce reference responses for two systems: the airborne SkyTEM system (Figure 56e-g) and the ground-based tTEM system (Figure 56h-j). These reference responses were computed by perturbing the subsoil models with varying temperature effects and setting a thermal diffusivity value of $1.0\text{e-}07 \text{ m}^2/\text{s}$. This enables the assessment of how different subsoil models account for temperature effects and how the system forward responses vary as a result. Figure 56e-j reports the percentage differences between subsequent in time forward responses, pointing the focus on the discrepancies arising when temperature effects are modelled from different subsoil models.

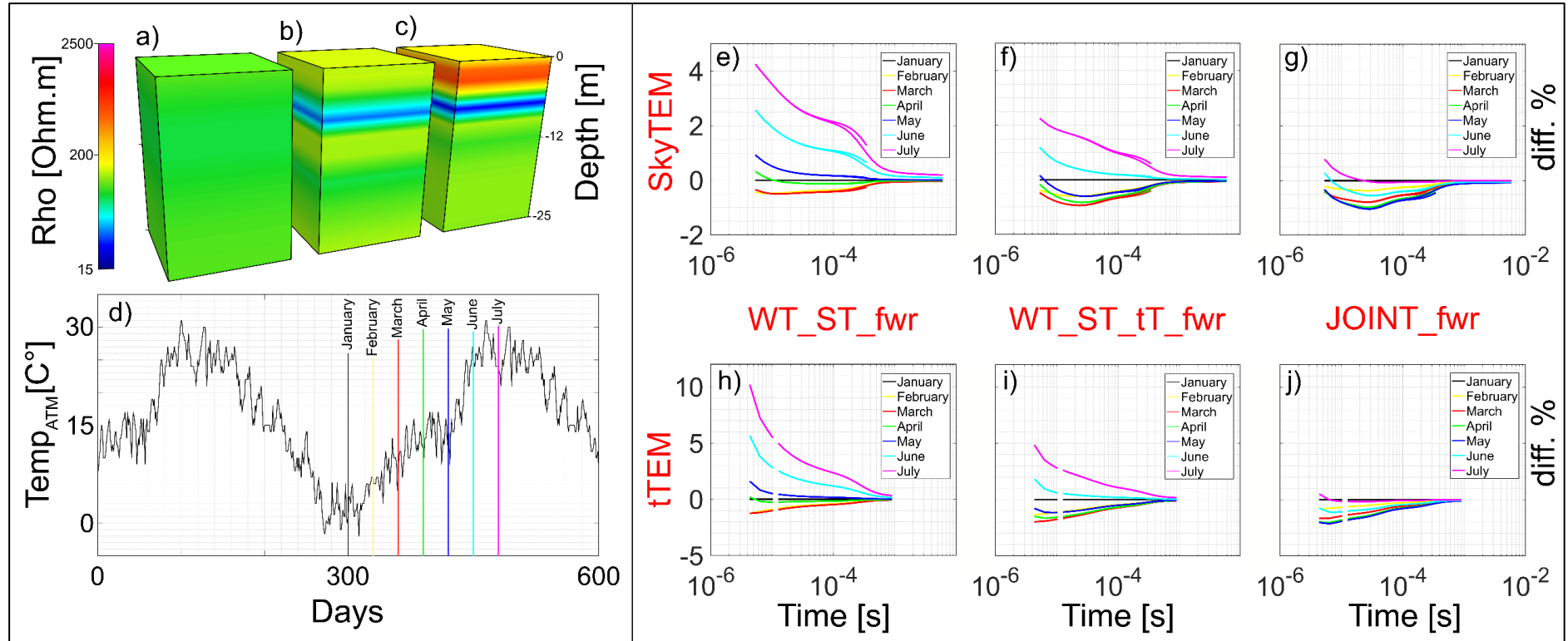


Figure 56: a-c) Subsoil models (0–25 m depth) used for forward response generation, derived from large TEM loop data only (a), inclusion of small loop data (b), and joint modeling with galvanic DCIP data (c). d) Measured atmospheric temperature data used to perturb the subsoil models for seasonal variation analysis, with colored vertical lines indicating computation times for the right panels. e-g) Forward responses for the SkyTEM AEM system over six months using subsoil models from large loop data only (e), small loop inclusion (f), and full joint modeling (g). h-j) Forward responses for the tTEM system with the same subsoil models: large loop data only (h), small loop inclusion (i), and full joint modeling (j).

For both systems, it is evident that the model derived from large-loop EM data alone, which is less resistive, results in higher temperature effects between responses across seasons, with differences exceeding 10% for the tTEM system. In contrast, using models that incorporate small-loop data and the joint model, characterized by higher resistivity in the shallow layers, reduces the EM transient discrepancies due to temperature effects to below 2% in the tTEM forward responses when using the joint model. These results remark first the importance of having highly resistive features in the EM calibration sites while emphasizing the necessity of having the most accurate subsoil model to avoid unprecise modelling of temperature effects. Specifically, to the Italian calibration site, the joint model reveals this high resistivity anomaly in the shallow layers, corresponding to the unsaturated zone depicted and validated also by the borehole measurements (Figure 10). The correct depicting of this feature results in a lower EM signal contribution in the forwarded signals from shallow high-resistivity regions, where temperature effects are more pronounced. Therefore, modelling the temperature effects using the most accurate subsoil model, is considered a foundational step in advancing EM system calibration. Practically, the proposed development aim at addressing the need of manufacturing companies to perform calibration at any time of the year, regardless of temperature conditions that may differ from those during the establishment of the reference model. The approach involves generating a reference signal from the joint model, accounting for the temperature conditions at the specific moment of the on-field measurement (Figure 56d). This ensures to have a reference signal that prevents over- or under-compensation in the system calibrations from temperature effects.

Moreover, to achieve accurate thermal modelling and compute the reference signal from the joint model, accurate site-specific temperature series and precise thermal diffusivity estimation are required. Ideally, these parameters should be measured at the calibration site. In the absence of direct measurements, a representative estimation of thermal diffusivity can be obtained using the procedure outlined in Section 2.1.2.3.

To conclude this section, seasonal variations at a site may not only involve temperature fluctuations. It is central that any significant changes expected at calibration sites are quantitatively evaluated in terms of their impact on the measured data. Calibration procedures must account for these changes in the reference response. For example,

hydrogeological changes, such as seasonal oscillations in the water table, can alter the model sensed by the system as well.

As previously mentioned, the ideal calibration site is a highly resistive one, as it prevents system issues from being masked by high signal levels and minimizes temperature effects. However, it is essential to ensure that no significant hydrogeological changes occur at the site, and to monitor them closely. Selecting a site with naturally low hydrogeological fluctuations, characterized by thick clay deposits in the shallow layers, would, on the other hand, introduce much stronger temperature effects than those observed at a resistive site. This would make rigorous calibration more challenging.

Therefore, the final recommendation is to use a highly resistive site with limited hydrogeological variations in the shallow layers and to implement temperature monitoring to account for temperature corrections in the calibration process.

3.2 THE CSIRO CALIBRATION LINE

In the previous section, we outlined the improvements aimed to be achieved when establishing calibration sites. Some of these involve the execution of the E&EM joint characterization of the site, and we discussed the various benefits that joint-characterized sites can bring to the overall AEM campaign. These benefits include their pivotal role as reference points for translating geophysical data into lithological units (see Section 1.4.1) and achieving the highest resolution for investigating areas of interest. Such sites can be particularly valuable in areas where structures or facilities are planned, thereby supporting on-field planning and execution activities.

Following the approach developed for the Italian calibration site (see Section 1.2.1), the same joint inversion methodology was applied during the period abroad as part of this Ph.D. project, conducted at the CSIRO headquarter in Perth, Australia. Specifically, the joint approach was used to characterize a section of the CSIRO AEM calibration line along a selected transect. The next subsection presents this characterization, highlighting the advantages of joint characterization in enhancing model resolution with its related implications.

3.2.1 THE GINGIN CALIBRATION LINE

The CSIRO calibration stretch for AEM systems is located in Western Australia, north of the city of Perth, near Gingin, within the Perth Basin. The Perth Basin is a north-to-north-northwest trending basin covering an area of approximately 170,000 km². Its sedimentary sequence extends along 1,300 km both onshore and offshore along the western margin of the Australian continent (see Figure 57).

The Perth Basin was formed during the pre-breakup continental extension between the southwestern continental margin of Australia and Greater India (Matte et al., 1997; Ali and Aitchison, 2005). This tectonic evolution began with a rifting phase in the Permian, followed by a period of post-rift subsidence and a multi-phase extension from the Middle Jurassic to the Early Cretaceous. This ultimately culminated in the breakup of Australia and Greater India. During the Late Jurassic to Early Cretaceous, the final rifting phase occurred in the onshore Perth Basin, leading to the present-day continental breakup (Norvick, 2003). This phase was accompanied by significant extensional faulting within the basin. Post-breakup, the basin undergone passive margin subsidence and regional westward tilting during the Early Cretaceous (Valanginian–Aptian; Quaife et al., 1994). Volcanic activity was localized in certain areas of the basin (Symonds et al., 1998; Gorter and Deighton, 2002;), while marine sediments were deposited in the more deeply subsided parts of the basin (Norvick, 2003). The Late Cretaceous and Cenozoic periods saw sedimentation occurring under stable, passive margin conditions, resulting in a cover of marine carbonates.

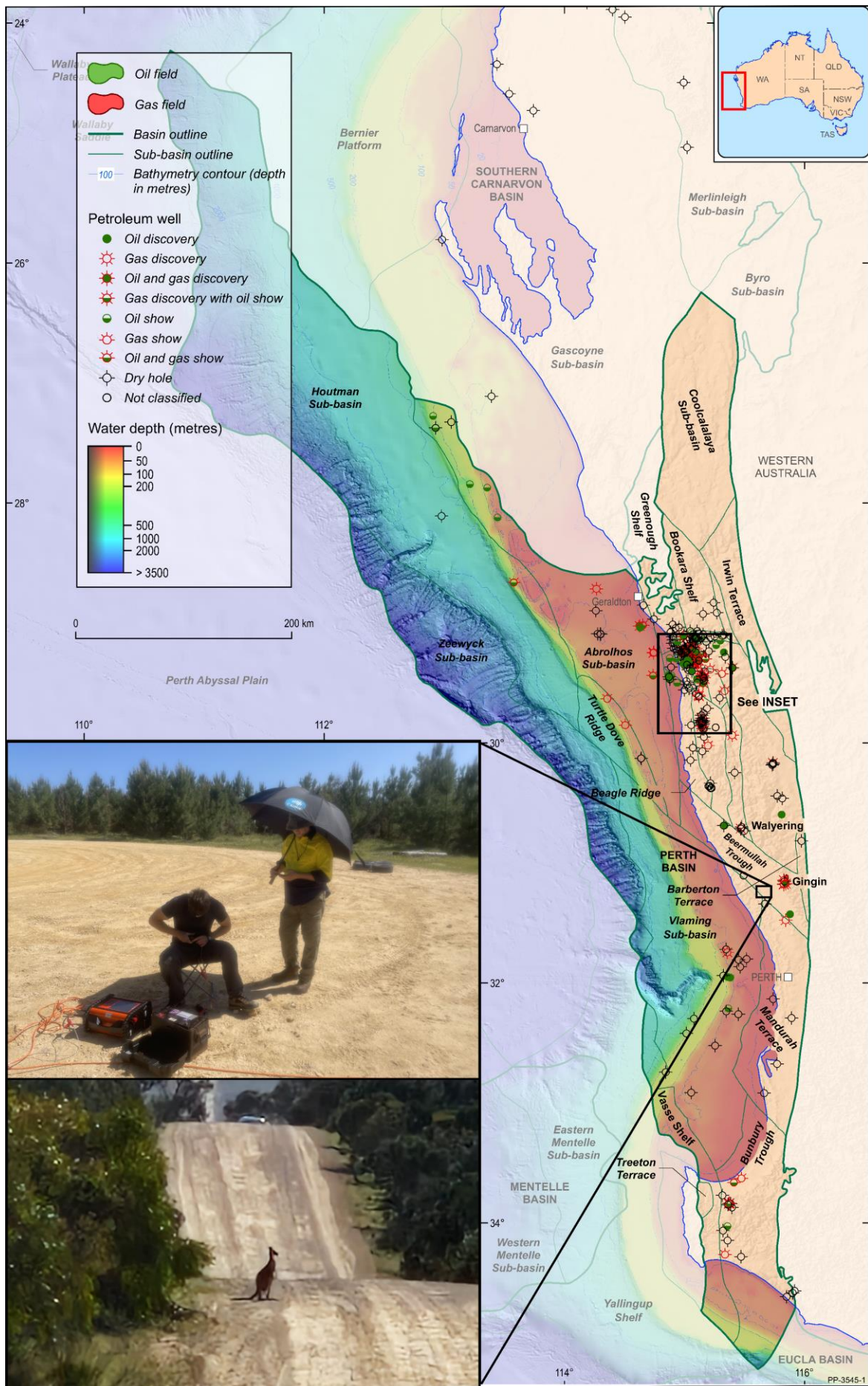


Figure 57: Map of the Perth Basin, covering approximately 170,000 km² along the western margin of the Australian continent. The field location along the Gingin Line, where fieldwork was conducted, is specified. Some images from field operations on the site are included. Image modified from its original version, sourced from Geoscience Australia.

3.2.2 DATA ACQUISITION AND PROCESSING

The data acquisition on the Gingin line focused on a part of the calibration stretch of 2.2 km where galvanic DCIP data and inductive ground EM data have been collected and Airborne EM data have been provided for the same piece of stretch by CSIRO.

The DCIP data have been acquired with a Terrameter LS2 system with an electrode spacing of 10 meters and employing a gradient protocol with acquisition settings identical to the ones used at the Italian calibration site described in section 1.2.1.4.

With the sTEM ground EM system (Figure 58a), 158 soundings were collected through the dual-moment energization strategy typical of this instrument. The system is operated in the profiler configuration (<https://www.temcompany.com/>), with the transmitter and receiver arranged in an offset geometry (10 meters apart) to facilitate a lightweight, portable acquisition process using a PVC frame. More specifically, the system features 3x3 transmitter and receiver coils. The transmitter has 2 turns, providing a total area of 18 m², while the receiver has 4 turns, resulting in a total area of 36 m². The dual-moment energization scheme is powered with a low moment characterized by 1 Amp of current and a high moment by 10 Amps.

The AEM data were acquired using the Tempest fixed-wing system (Lane et al., 2000), which features an offset configuration with a horizontal separation of 110 meters and a vertical displacement of 49 meters between the transmitter and receiver. The system operates with a base acquisition frequency of 25 Hz. The transmitter is mounted around the aircraft body (Figure 58) and covers a total area of 153.53 m² (1 turn). It operates with a 50% duty cycle, injecting 660 Amps into the transmitter to generate a peak moment of 101,330 Am². Data are sampled at 76.8 kHz using a receiver housed in a towed bird. The receiver includes three components capable of measuring variations in the secondary magnetic field in three axes. The system outputs measurements reaching 11-milliseconds with output windows generated by stacking 200-millisecond intervals (approximately 12

meters at typical aircraft surveying speeds), during which over 1500 samples are collected per half-cycle.

The Tempest system measures the dB/dt field in offset configuration, but the signal undergoes a pre-processing phase carried out by the data provider that removes the effect of the system response and of the primary field, and reconstructs a B-field 100% duty-cycle signal as output. The accuracy of this procedure is achieved measuring accurately the positions and the attitude of both transmitter and receiver during the acquisitions.

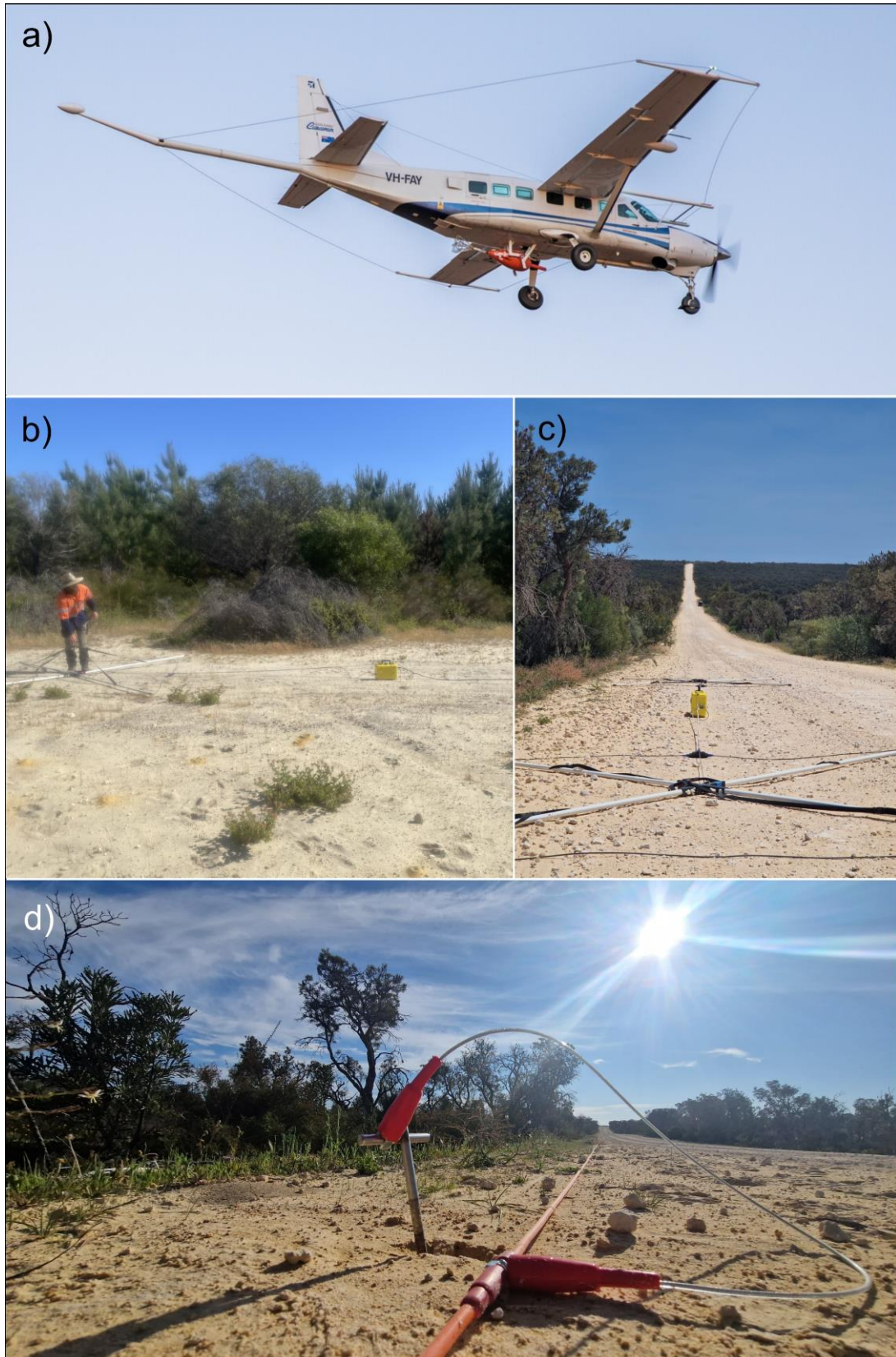


Figure 58: Geophysical systems used for data acquisition along the Gingin Line: (a) Tempest fixed-wing airborne EM system, (b-c) sTEM EM system in the profiler configuration, and (d) electrode, jumper and cable during the galvanic DCIP acquisitions

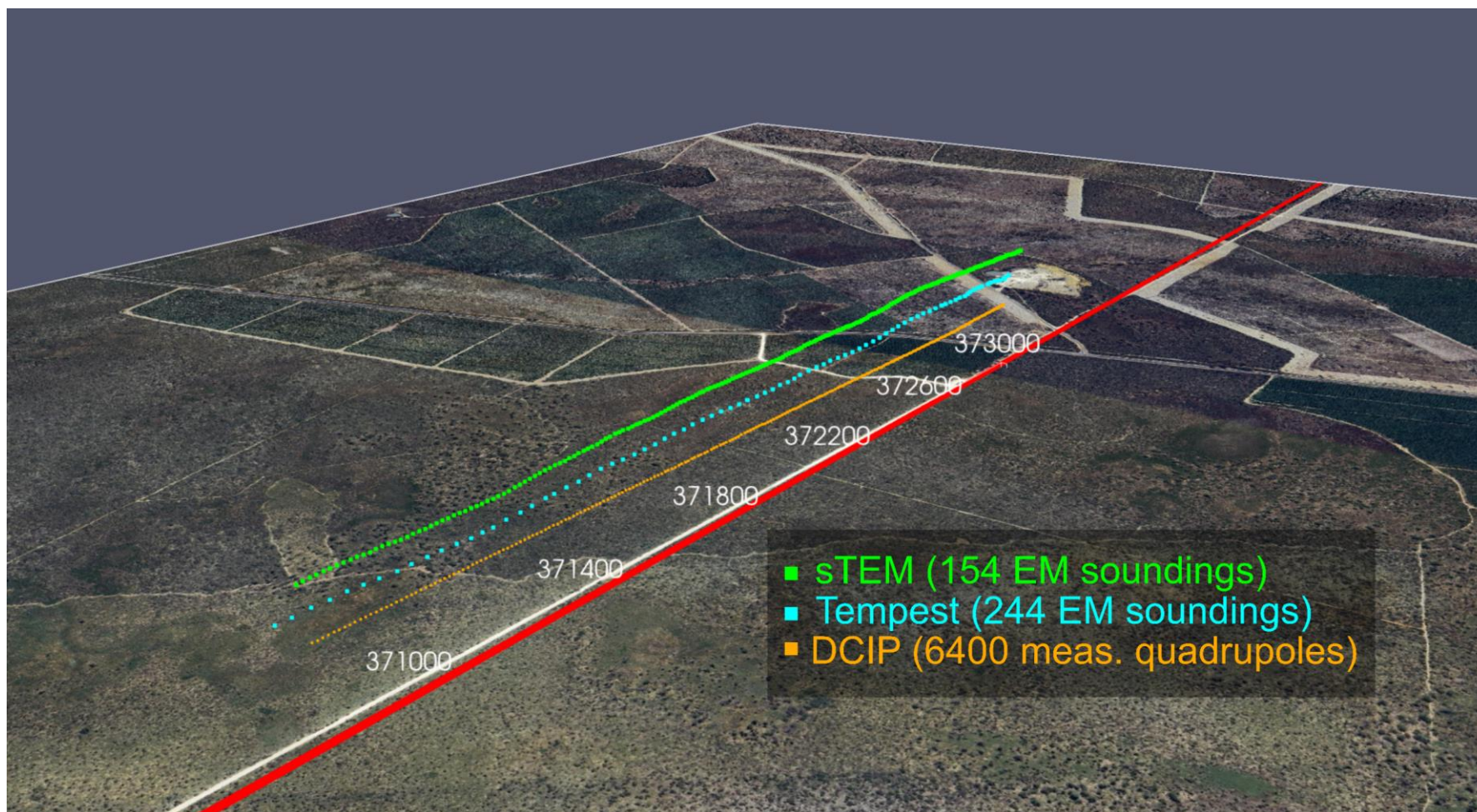


Figure 59: Map of the Gingin Line showing the locations of inductive and galvanic geophysical measurements.

Prior to the modelling phase, all acquired data underwent accurate processing. For the EM data, manual cleaning was performed on both sTEM and Tempest datasets to remove noise gates and assess potential signal coupling with nearby structures. Figure 60 illustrates the processing applied to the two datasets: the grey areas in the panels represent the removed gates, while the blue areas indicate the retained signal. It is worth noting that the EM measurements at the eastern side of the transect were entirely removed due to the presence of a highway, a powerline, and a metal shelter. The affected signal was excluded until their influence was completely absent. The ground-based sTEM data were more severely affected by coupling with the small metal shelter (Figure 60, panel c) since they had been acquired closer to it compared to the airborne Tempest system, which operates at a cruise altitude of 120–140 meters. This is evident when comparing Figure 60 panel a and b: the sTEM data required a slightly longer signal removal along the transect. However, just east of the metal shelter, all data also from Tempest had to be discarded due to strong coupling with other structures at the eastern edge of the line (evident also in the models during the inversion phase, therefore removed).

Similarly, for the DC measurements, the dataset was carefully processed to manually remove outliers detected along the entire profile (Figure 61). In contrast to the EM data, the galvanic measurements did not exhibit any systematic disturbance issues, neither in the DC nor in the IP components. This is evident also in the IP decay curves shown in the right panel, which were selected from the eastern beginning of the profile. The absence of disturbances can be attributed to the sufficient distance of the highway from the start of the profile and the fact that the metal shelter had no grounded metallic components.

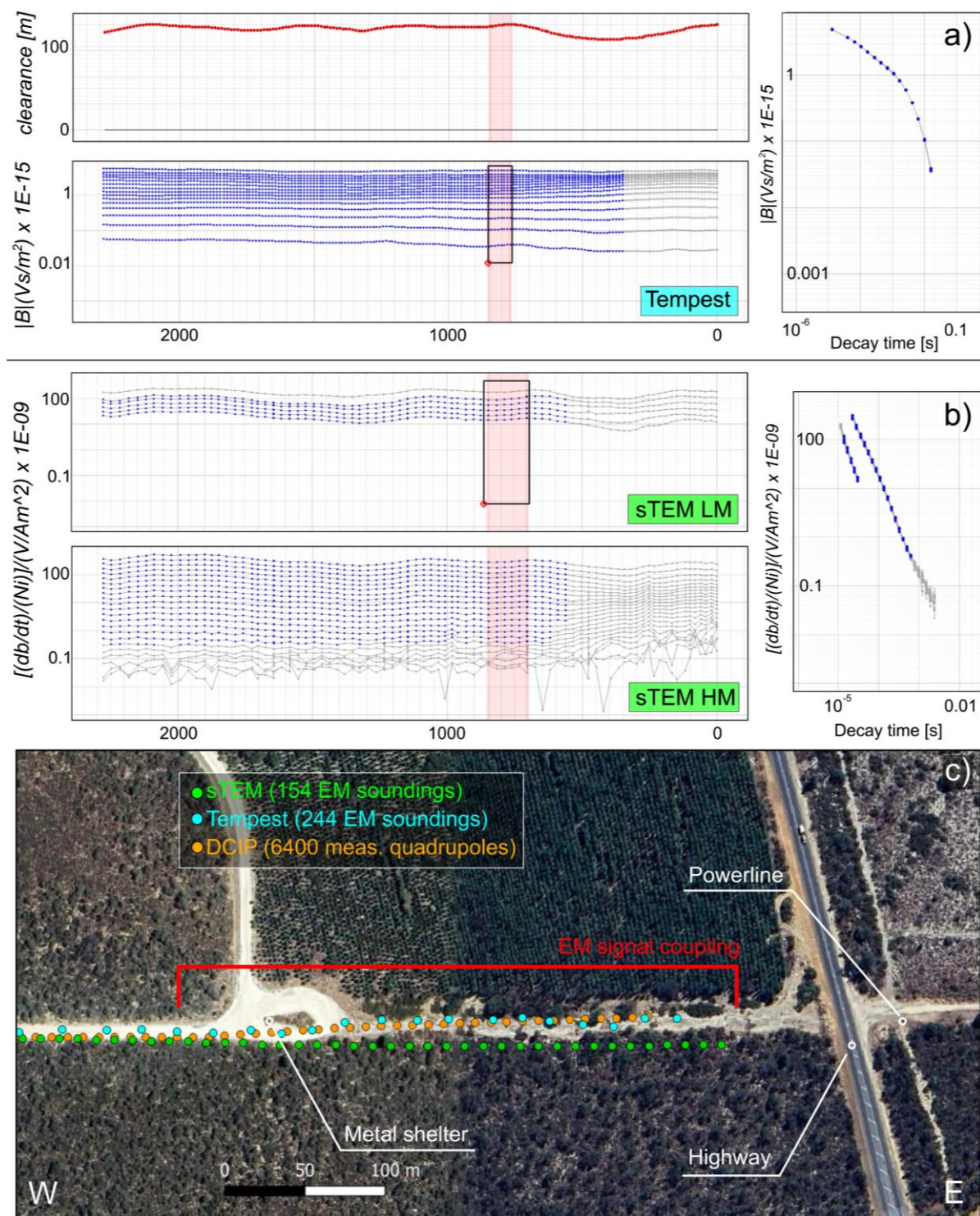


Figure 60: Tempest (panel a) and sTEM (panel b) inductive data, with details on the eastern edge of the Gingin Line, where some data (grey points and gates) were culled due to coupling with anthropogenic infrastructure (panel c).

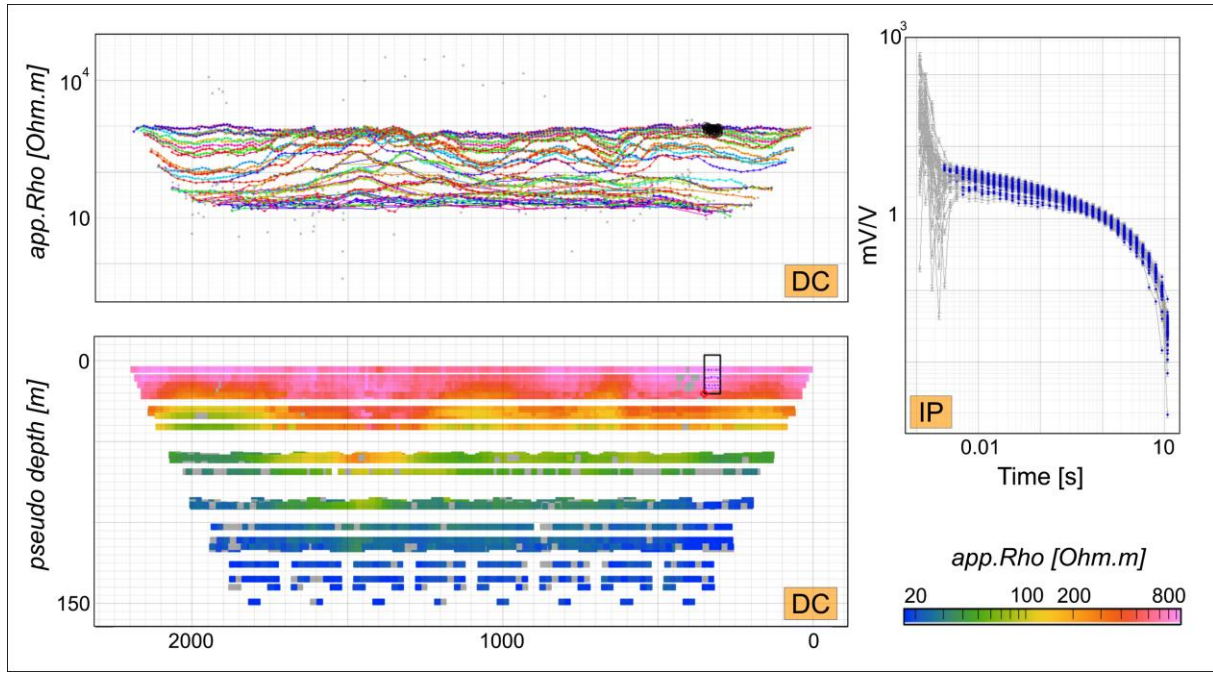


Figure 61: Gingin acquisition of galvanic direct current (DC) data, displayed as a pseudosection, along with induced polarization (IP) decays extracted from the eastern part of the profile, as indicated by the black square.

3.2.3 DATA MODELLING, VALIDATION AND INTERPRETATION

The modelling of the data acquired along the Gingin line followed the same approach used for the inversion of the data presented in Section 1.2.1.4. Initially, independent inversions were performed to ensure a proper fit for all datasets and meaningful results that align with the sensitivity and resolution characteristics of each system.

Once this phase was completed, the entire dataset was integrated into the unified data space of the joint inversion framework in which, for both inductive and galvanic modelling, the full transfer function was incorporated including system geometries, filter characteristics, and waveforms.

Both inductive and galvanic data are modelled in frequency domain, with 1D computations for inductive data (Ward and Hohmann, 1988) and 2D computations for galvanic data (Fiandaca et al., 2013).

The independent inversions of the EM data from sTEM and Tempest (Figure 62, panels a and b) and the galvanic data (panel c) were performed first. Only after achieving satisfactory results in the independent modes, the joint inversion was set. The joint framework construction followed a similar approach to the ones presented previously

(e.g., Sections 1.2.1.4 and 1.4.2). First, independent forward meshes are defined for the different data groups: 1D meshes for inductive data and 2D meshes for galvanic data (see Fig. P1_1). The connection between the model and forward meshes was then established by interpolating the model parameters onto the forward mesh discretization.

Moreover, the EEMverter feature of splitting the inversion into multiple cycles (see also Fig. P1_2) is utilized again in this joint modelling process, as it has proven effective in improving inversion convergence, achieving a good data fit, and enhancing the meaningfulness of the output model. The inversion is initialized with the small-coil EM measurements (sTEM) in the first cycle, allowing the model to depict the shallow structures. In the second cycle, the large-coil EM data (Tempest) were introduced, enhancing sensitivity to deeper parts. Only after full convergence of the second cycle were the galvanic DC data groups included, leading to the joint inversion of the E&EM data.

Figure 62 presents the models obtained from both the independent and joint inversions, while Table 13 provides the corresponding misfit values. The table includes the misfit from the independent inversions, the final misfit from the joint inversion process, as well as the intermediate misfit values from each sub-cycle in the joint modelling. Moreover, Figure 63 presents the spatial distribution of the misfit, showing the misfit for each sounding of the airborne and ground data and for each quadrupole in the pseudosection of the galvanic data.

Table 13: Misfit of the sTEM, Tempest, and DC datasets from independent and joint inversions, including intermediate cycles leading to the final model integrating all inductive and galvanic data.

MISFIT		sTEM	Tempest	DC
Independent		1.0	1.1	2.3
Joint	Cycle_01	1.0	/	/
	Cycle_02	1.1	1.2	/
	Cycle_03	1.4	1.7	1.8

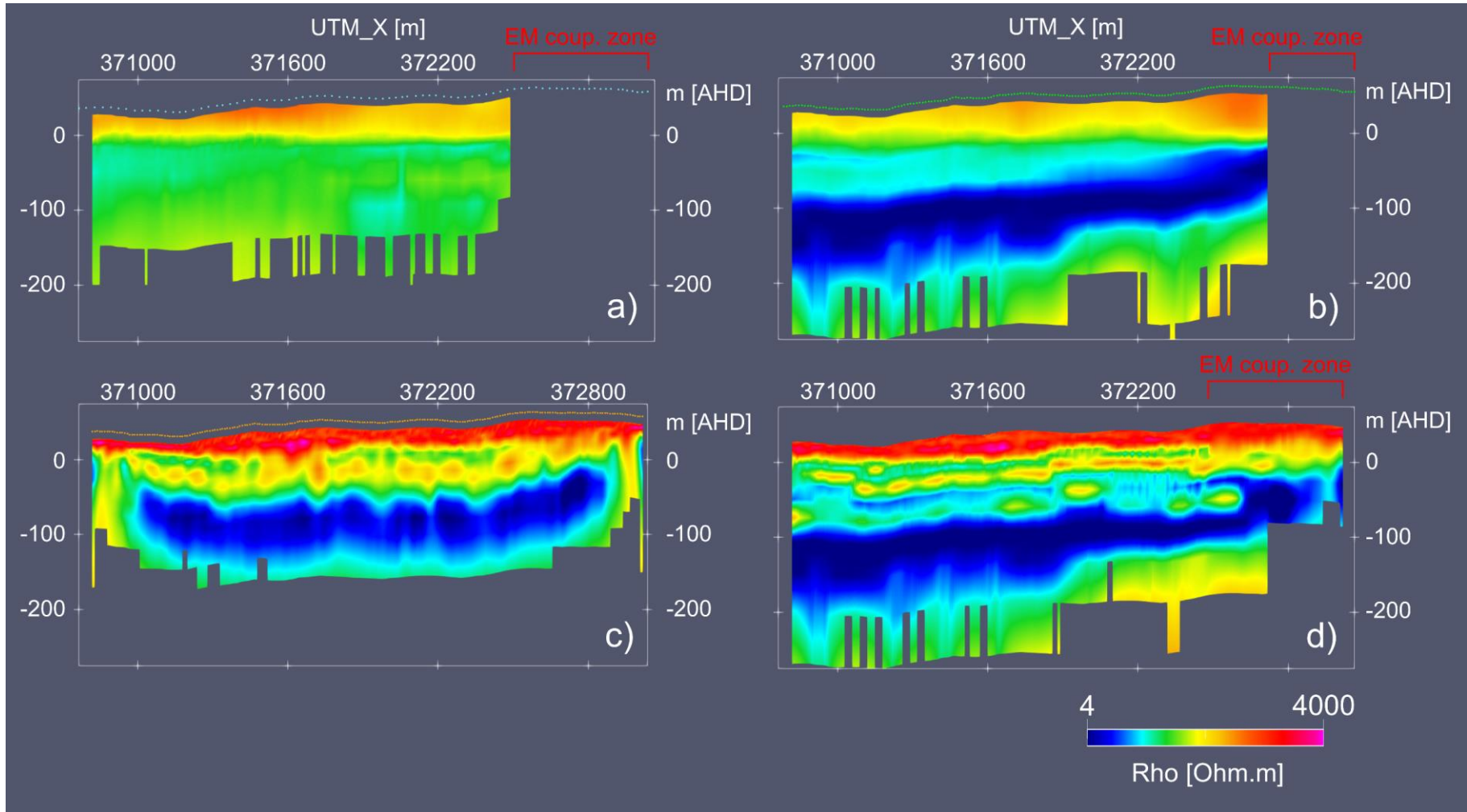


Figure 62: Models from independent and joint inversion of Gingin Line data: (a) sTEM inductive, (b) Tempest airborne inductive, (c) DCIP galvanic, and (d) joint model combining all datasets. Data positions are shown on top, with red intervals marking removed inductive data due to coupling.

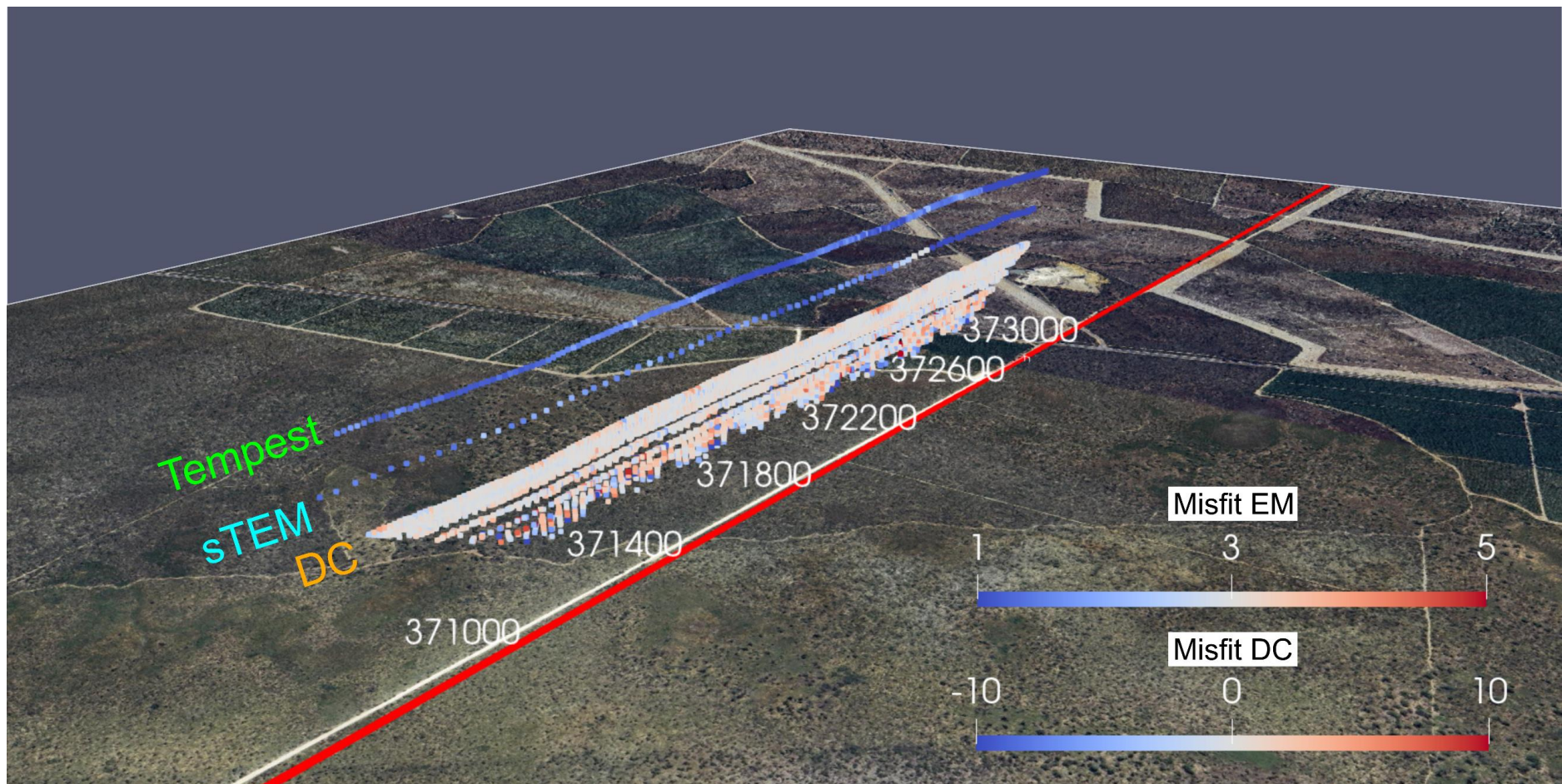


Figure 63: Misfit distribution along the Gingin Line for the inductive (lines) and galvanic (pseudosection) datasets from the joint inversion modeling.

The comparison of the models in Figure 62 shows that the EM independent models (panels a and b) exhibit the typical enhanced sensitivity of EM data to low-resistivity features, resulting in a smoothed representation of shallow high-resistivity structures compared to the galvanic model (panel c) also estimating lower resistivity values. The galvanic model provides a more defined characterization of the shallow high-resistivity cover and also identifies a second high-resistivity anomaly at around -25 meters of elevation, located between two lower-resistivity anomalies. The joint model (panel d) shows improved resolution compared to any independent model, successfully incorporating the resistivity features present in the independent models and delineating additional layers that were not resolved in either E&EM independent inversions. The higher resolution achieved through the joint inversion, compared to the independent models, is consistent with the findings presented in Sections 1.2.1.4 and 1.4.2. This improvement can be attributed to the successful construction of a balanced inversion framework with a unified data space, effectively merging the sensitivities of different data types (see Figure 11). As a result, the total sensitivity is enhanced, allowing for a sharper definition of the structures already identified by the independent models while localizing new electrical anomalies. The effectiveness of merging these sensitivities is further appreciable when observing the right portion of the joint model in panel d. In this area, corresponding to the coupling zone of the EM systems (Figure 62), the removal of all EM data results in a noticeable loss of resolution. Consequently, in this region, the inversion sensitivity is comparable to the one of the galvanic data.

To validate the retrieved model beyond the misfit analysis, a borehole comparison is deemed necessary. Although no deep borehole information is available directly along the surveyed stretch, two boreholes are present in the surrounding area. These boreholes are displayed in both the independent and joint models in Figure 64, where they have been reprojected from their original positions to overlap with the profile.

The first borehole (Bhl_9374039) is located approximately 500 meters northwest of the left end of the profile. It includes lithological description for the first 37 meters from the surface, revealing a limestone formation extending to a depth of 30 meters, followed by a transition to a clayey sand lithology down to the borehole bottom. The second borehole (logEM_NGc) is located 12 km east of the measured stretch. EM logging measurements were conducted within this borehole with a measurement spacing of 10 centimetres,

providing a high-resolution characterization of the distribution of electrical properties to a depth of 115 meters.

The first borehole (Bhl_9374039) is displayed at the profile point closest to its original position. Despite its limited depth, it allows validation of the first lithological transition in the joint model, specifically from the shallow high-resistivity anomaly to the first lower-resistivity anomaly. In the independent models, this transition is also depicted correctly, in accordance with their respective resolution. However, the EM independent models exhibit a smoother transition compared to the joint model, while the DC independent model positions the low-resistivity anomalies slightly to the right of the borehole reprojected location.

The second borehole (logEM_NGc) was included in the profile despite its considerable distance from the surveyed stretch, not to validate specific layers of the model directly, but rather to demonstrate that the litho-stratigraphic alternations observed in the log-EM measurements are plausible within this area.

Although the borehole is located far from the profile, it lies within the same geological domain, where lithostratigraphic and structural characteristics can be considered consistent. These features, however, are not distinctly depicted in the independent models due to their limited resolution and sensitivity (Figure 64, panels a-c).

In contrast, the joint model (Figure 64, panel d) appears to capture a vertical alternation of geological structures that aligns with the patterns observed in the log-EM measurements. This is precisely the reason for overlaying the borehole on the profile despite its considerable distance, demonstrating that this is the geological architecture that should be expected and targeted at the site.

Regarding the vertical positioning of this borehole, we aligned it with the first geological boundary in the section—specifically, where the transition from the high-resistivity Surficial Formations marks the shift to what is likely the underlying Cretaceous sequence, as these units originate from different depositional and deformational processes. This alignment was deemed a reasonable choice, considering both the lithological characteristics and the elevation difference between the profile and the borehole, which needed to be accounted for. To further highlight the differences in resolution between the independent and joint models, 1D models were extracted from a location near the

logEM_NGc borehole for all independent and joint inversions. These extracted models are presented in Figure 65 for comparison.

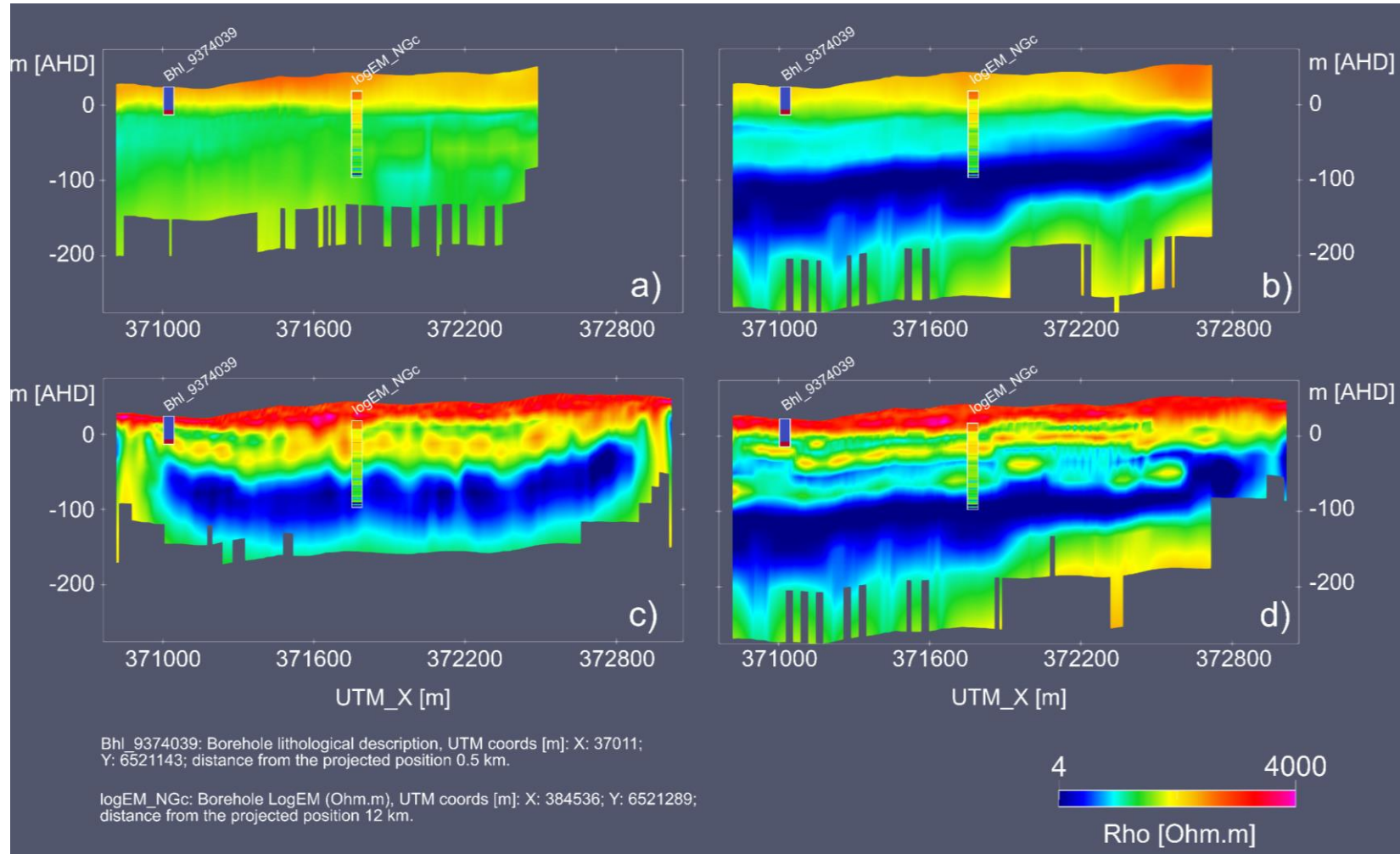


Figure 64: Models from independent and joint inversion of Gingin Line data: (a) sTEM inductive, (b) Tempest airborne inductive, (c) DCIP galvanic, and (d) joint model integrating all datasets, now overlaid with borehole data—Bhl_9374039 providing lithological information and logEM_NGc displaying resistivity values.

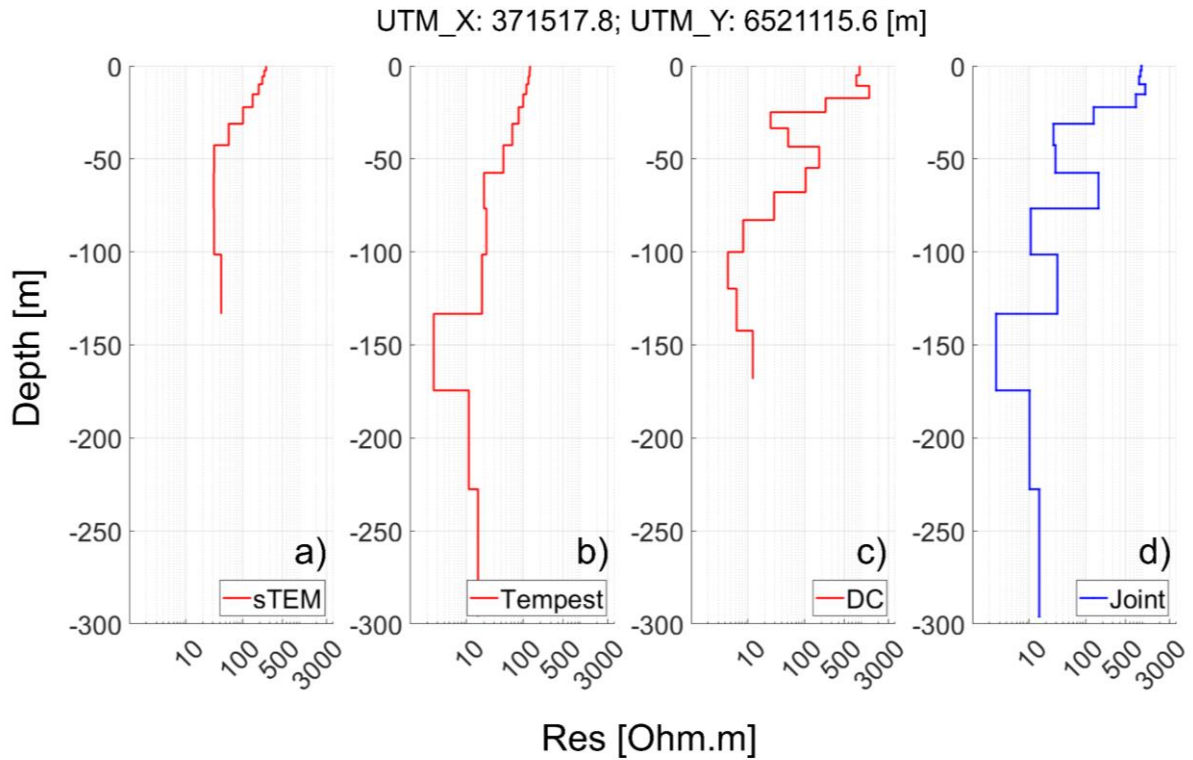


Figure 65: 1D model extracted from the closest position to the borehole logEM_NGc (Fig. 32), respectively from (a) sTEM model, (b) Tempest model, (c) galvanic DC model, and (d) joint model.

Regarding the primary objective of Section 3.1—advancing the establishment of reference and calibration sites—it is evident from the validated models that joint inversion significantly enhances model resolution, thereby directly improving the potential accuracy and reliability of seasonal temperature effect modelling for future system calibrations conducted under different thermal conditions. However, the improvements in temperature modelling using independent versus joint models are not expected to be as pronounced as in the Italian reference site example. On the Gingin line, temperature effects will likely be confined to the shallow high-resistivity and highly homogeneous domain, which is already reasonably well depicted by all models. This makes the Gingin line an optimal calibration site for EM systems, which should not show significant temperature-related seasonal variations

Conversely, regarding the use of this stretch as a potential reference line for the interpretation of AEM campaigns, as in the case presented in Section 1.4.1, having the joint model would make a significant difference, providing a high-resolution translational tool from AEM models to lithostratigraphic information. This would allow for an initial

assessment of which geological structures can actually be resolved by the specific AEM system and, subsequently, establish a bridge from the AEM model to the joint model and, ultimately, to the geological interpretation. In doing so, it leads to a more informed interpretation of subsurface structures. To illustrate this final step from the geophysical model to the geological interpretation, Figure 66 presents the geological interpretation of the joint geophysical section. The enhanced resolution of the joint model, compared to the independent ones, has allowed the identification of multiple layers that, as already said, were not evident in the independent models. Specifically, Figure 66 interprets the high-resistivity shallow cover as belonging to the Surficial Formations, such as the Tamala Limestone formed in the Cenozoic era. Further below, the first lower-resistivity anomaly is interpreted as the Late Cretaceous Lancelin Formation, followed further down by the Early to Mid-Cretaceous members of the Osborne Formation. At greater depths, the section transitions into the Early Cretaceous depositional units, represented by the two members of the Leederville Formation, with the Wanneroo Member marking the bottom of the interpretation, as it corresponds to the maximum depth reached by the model. Additionally, by analysing the lateral relationships of the resistivity anomalies, it has been possible to theorize the presence of three faults within the section. All three faults exhibit extensional features, aligning with the extensive deformation style that occurred during the Early to Mid-Cretaceous eras in this area.

Moreover, beyond their role in interpretation, the joint results further demonstrate their applicability as a valid high-resolution investigation tool, even in this geological environment. In fact, it would provide the highest resolution for characterizing sites where specific solutions and infrastructures are planned to be built, as exemplified in Section 1.4.2. This can be a valid advance in the follow-up refinement of the AEM campaigns, targeting the best spatial description of the geological architecture, key aspect when planning infrastructure developments.

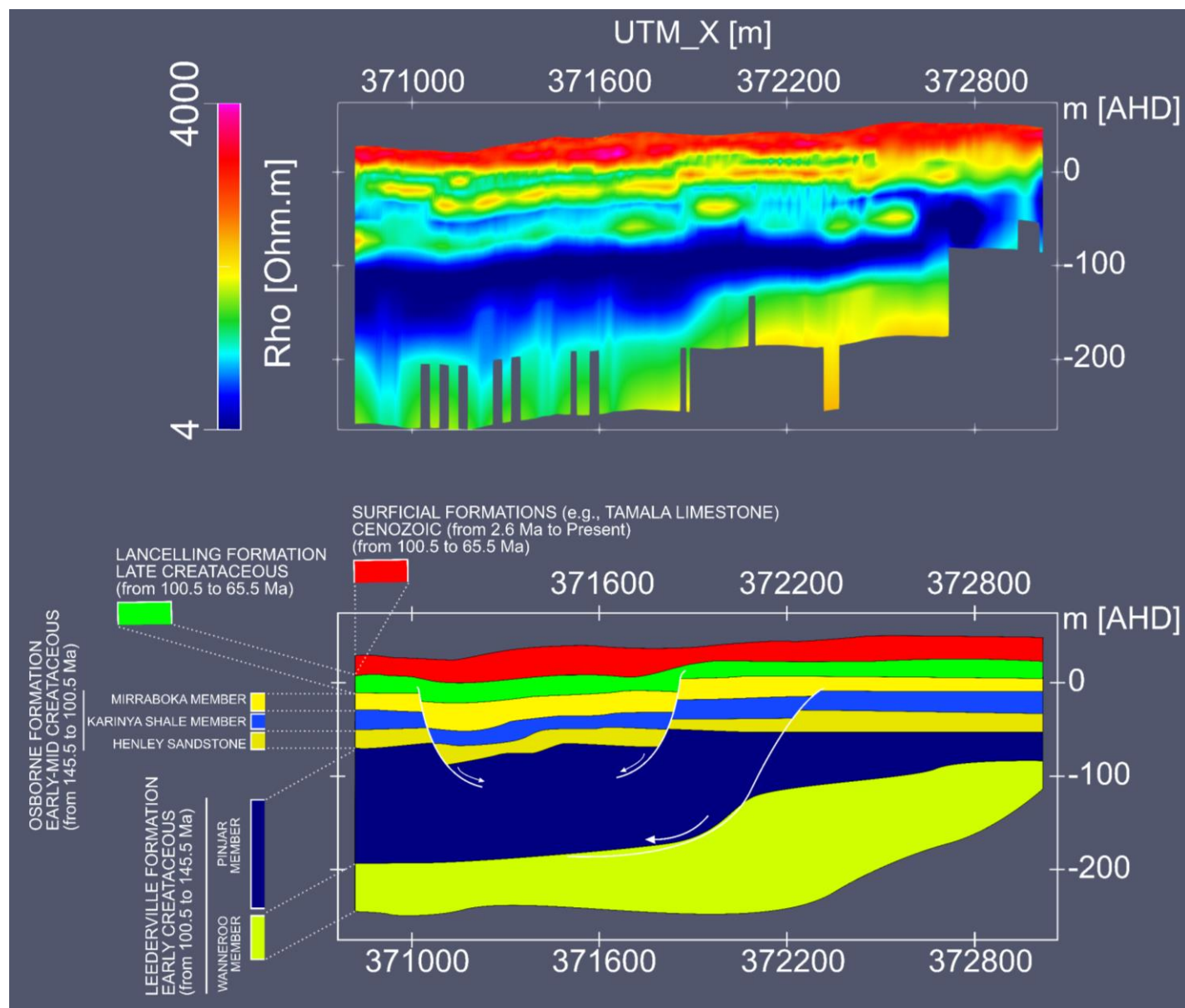


Figure 66: Geological interpretative section of the joint model derived from inductive and galvanic geophysical characterization and modeling along the Gingin Line. The upper section shows the joint model, while the lower section presents its interpretation, highlighting lithostratigraphic and structural elements.

CONCLUSIONS

The Ph.D. project stemmed from the research objectives of advancing the state of the art in the calibration of electromagnetic (EM) systems, particularly Airborne EM (AEM), and improving the practice in establishing reference sites for interpreting AEM campaigns. This need initially arose from the execution of the largest AEM campaign ever carried out in Italy between 2021 and 2023, in the northern part of the country. The campaign aimed to investigate the geological and hydrogeological architecture across large, medium, and small scales, serving as the foundation for long-term management solutions in the region. A key component of the Ph.D. schedule was the establishment of the HydroGeosITe within the survey area. This high-resolution reference site was designed to bridge large-scale geophysical models from the AEM survey with lithostratigraphic interpretation. The site characterization relied on an extremely dense geophysical survey supported by the execution of a deep borehole, to achieve the best possible correlation between geophysical and geological data. This correlation was then intended to extend to the broader campaign area, enhancing the interpretation of AEM survey results and their reliability. Additionally, the HydroGeosITe was envisioned as an innovative calibration site for EM systems, particularly AEM, setting a new standard for calibration in Italy. The goal was to establish a long-term reference facility that could support future AEM campaigns across the country, ensuring accuracy and consistency among subsequent investigation campaigns.

Consequently, the Ph.D. project began with the characterization of HydroGeosITe using both Electrical and ElectroMagnetic (E&EM) methods. The primary objective was to achieve an extremely dense site characterization (Section 1.2.1.4) by employing multiple E&EM systems, covering a wide range of data sensitivities and measurement frequencies. This has been achieved utilizing different instruments, capturing that way the geological structures at various scales to address their spatial variability and great heterogeneity. Then, the first research outcome focused on modelling this E&EM data coverage in an innovative way to increase the subsoil characterization resolution. To this end, a novel E&EM joint inversion procedure was developed, integrating both data types within a unified framework. This approach proved capable of depicting subsurface electrical

anomalies with unprecedented resolution, outperforming the independent galvanic and inductive investigations. The procedure had been successfully applied at HydroGeosITe and validated at the site through borehole data comparison. A comprehensive discussion of these developments is presented in Section 1.2.1, which includes the full version of the first scientific paper produced during the Ph.D. The joint modelling, with its enhanced resolution, thus provided a new level of translation from geophysical to geological information. To further strengthen this correlation at HydroGeosITe—and given that the E&EM geophysical coverage at the site featured a 3D distribution—the guidelines for establishing the reference site were derived from a study that expanded the high resolution of the joint 2D models into a full 3D volume for the entire site (Section 1.4.1). This advancement allowed for a precise definition of the three-dimensional morphology of the lithostratigraphic structure in the subsurface. In this context, accurately delineating these structures was crucial for recognizing specific geological units, where geometrical recognition of depositional patterns played a key role in distinguishing them.

After developing the joint inversion approach, it was necessary to assess its performance across different sites and geological contexts. The first additional application was conducted within the Italian AEM campaign area (1.4.1). In this study (Section 1.4.2), we conducted a 3D E&EM survey across the entire area of interest. The results confirmed the superior performance of joint inversion compared to independent methods, providing a high-resolution depiction of subsurface structures. This level of detail enabled a completely new approach to infrastructure planning, where accurate knowledge of geological boundaries, their spatial variability, and the extent of the target formation—in this case, the first aquifer suitable for hosting the injection and possible protecting aquicludes—was crucial.

Another major research topic, addressed primarily in the second part of this thesis and during the later stages of the Ph.D., focuses on E&EM temporal analysis studies. These studies range from investigating specific challenges in temporal analysis to leveraging the achieved improvements to further advance the state of the art in calibration procedures for EM systems.

In particular, the effects of seasonal temperature variations were studied in a long-term monitoring survey using galvanic data, as reported in Section 2.1.2, which includes the full version of the second scientific paper produced during the Ph.D. In this case,

temperature oscillations completely obscured the target anomalies representing the monitored processes, leaving the data unusable. To address this issue, a novel inversion scheme was developed to filter temperature effects from the models. This approach involves inverting for the thermal diffusivity of the ground without requiring direct temperature measurements at the time of data acquisition. As a result, the survey was successfully recovered, producing accurate results with temperature effects removed and the models validated using ancillary information. This development provides the geophysical community with a tool for recovering monitoring experiments that lacked thermal monitoring at the time of acquisition underestimating the magnitude of temperature effects.

After completing this work and observing the strong influence of temperature on resistivity measurements obtained with galvanic instruments, it was grasped that seasonal temperature variations could similarly affect the subsurface model at sites where EM instrument calibrations are conducted. Since calibration is not always performed at the same time of year, these variations may introduce significant differences in the resistivity model within the first several meters—typical of seasonal temperature variation depth—potentially impacting the calibration process. In fact, the common practice involves measuring with the instrument under calibration at the site and then adjusting the recorded signal against a reference signal, which may have been collected at a different time of the year under different thermal conditions. As a result, variations in subsurface resistivity distribution could affect the accuracy and consistency of the calibration.

This led to the next advancement in EM calibration, where the modelling of temperature effects in different calibration activities was addressed. The potential impact of seasonal temperature variations on calibration procedures is first explored in detail in Section 2.1.3, highlighting the risk of adjusting EM signals for thermal conditions rather than actual hardware differences between instruments.

A deeper analysis of this issue is presented in Section 3.1, where temperature effects on calibration are shown to be even more significant than other parameters of the system transfer function, which are typically given primary consideration during calibration. This section also details the application of the joint inversion procedure as an important tool for characterizing the calibration site and providing the reference model from which the

reference signal for calibration is generated. Specifically, it enables the retrieval of the most accurate subsurface resistivity distribution, which directly improves the accuracy of thermal modelling. This, in turn, allows for the precise correction of undesired temperature-induced resistivity variations. In this section, it is demonstrated that characterizing the calibration site with a joint model prevents errors in temperature corrections during calibration accuracy, ensuring precise adjustments without over or underestimating thermal effects. Consequently, this approach avoids excessive or insufficient signal adjustments during calibration, as could occur when relying on independent models instead of the joint one.

Still on the topic of temporal analysis, during the Ph.D. period abroad hosted by CSIRO in Perth (Australia), these studies continued, this time focusing on a AEM temporal dataset collected in Southern Australia, which led to the production of the third scientific paper of the Ph.D., reported in Section 2.1.4. The dataset was modelled to investigate the hydrogeological evolution of a hypersaline floodplain and its freshwater recharge. For this study, a new time-lapse inversion framework was developed specifically for inverting airborne EM datasets. At the time of writing, this represents, if not the first attempt in this direction, one of the first. The main challenges arose from the lack of reference methodologies, requiring the definition of a novel approach from data processing to modelling. For instance, the temporal datasets presented specific noise issues between repeated surveys, necessitating the development of a new processing workflow. Another challenge was the non-coincident soundings between surveys, despite efforts to maximize overlap during acquisition. To address this, a specific architecture for forward and time-lapse model meshes was defined. Additionally, improving the accuracy of system flight altitude estimation was crucial for obtaining detailed and reliable results in the shallow subsurface. These advancements led to the successful detailed study of the floodplain evolution in terms of freshwater exchange. The results enabled both spatial and precise volumetric analyses of freshwater distribution across the floodplain, and their validation was carried out through an independent hydrological analysis, which revealed a strong match with the geophysical results. However, the geophysical time-lapse models provided a significant advantage over hydrogeological analyses, which were constrained to point measurements along the river, limiting spatial exploration and representativeness. Furthermore, the effects of temperature variations on the dataset were assessed. It was

found that no significant temperature changes occurred between surveys that could have introduced variations in the subsurface model comparable in magnitude to those caused by hydrogeological processes. This was primarily due to the AEM surveys being conducted in nearly the same period of the year, as well as the fact that the temperature variations were too small to be detected at the resolution of the AEM system used for the measurements.

The time-lapse modelling of AEM data and the results obtained provided new insights into natural processes, adding a whole new dimension of information. The development of new tools for modelling AEM time-lapse surveys, combined with the results achieved, supports the application of this approach to further enhance the understanding of physical phenomena in other case studies and real-world field environments.

Furthermore, building on these advancements and aligning with the Ph.D. research objectives, the development of the time-lapse AEM modelling scheme provides a tool for integrating multitemporal acquisitions into future AEM campaigns. These datasets can now be effectively modelled and interpreted, opening to new investigative possibilities.

Finally, in the concluding phase of the Ph.D., during the research period abroad in Australia, the joint investigation approach was applied to characterize the AEM calibration line of CSIRO, located outside Perth (Section THE CSIRO CALIBRATION LINE). This provided another opportunity to further investigate the capabilities of the developed joint procedure in a completely different geological environment, where it once again proved to outperform independent modelling in terms of resolution. On this calibration line, the availability of the joint model has the potential to enhance the accuracy of the calibration activities. Additionally, the concept of a reference site for supporting interpretation applies here as well, serving as a key location for translating geophysical data into lithological information—particularly for AEM projects within the same geological region. In this context, an example of the translation from joint geophysical models to lithostratigraphic interpretation is provided.

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In conclusion, this Ph.D. research began with the goal of advancing the state of the art in the establishment of calibration and reference sites for E&EM instruments. This objective was achieved through extensive field acquisitions, followed by detailed analyses and

research activities, leading to the development of new modelling schemes, protocols, and best practices.

However, looking at the entire process, it appears that the technical advancements developed to achieve these improvements may have an even greater impact than the original research goals, possibly influencing both scientific research and professional practices at a broader level. We believe that the joint inversion procedure developed and validated during this Ph.D. has the potential to represent a turning point in E&EM high-resolution investigations within the first 500 meters. This thesis has presented three key applications of this joint methodology, yet its use has already been extended to various geological environments and different investigation targets. In all cases, the results consistently show significant improvements over independent inversions, maintaining the same level of enhancement demonstrated in the examples provided.

Furthermore, we strongly believe that joint inversion can represent a new valuable tool not only as a standalone method but also integrated with AEM surveys. The combination with AEM campaigns can be used to investigate specific sites of interest, previously identified in large-scale surveys, delivering unprecedented resolution in both 2D and 3D subsurface characterization. This application is believed possible also considering the joint investigations fast execution times, requiring only a few weeks from data acquisition to result delivery, and at a relatively low cost compared to the total AEM project budget. Another key contribution of this research lies in the improvements proposed for temporal analysis studies, particularly in addressing the impact of atmospheric temperature oscillations, which are often overlooked in monitoring studies but can lead to erroneous interpretations. The tools developed in this work directly tackle this issue while also opening new possibilities for high-accuracy time-lapse studies using both E&EM data. The AEM time-lapse study presented in this thesis, beyond its inherent innovation, serves as a key example also of this approach. Before interpreting subtle variations in the temporal models, thorough verification was conducted to rule out temperature-related effects, which otherwise would have been compensated. Only after confirming that the observed changes were not influenced by temperature differences were the models and their interpretations accepted and delivered, establishing a solid foundation for future AEM time-lapse studies, along with the inversion scheme developed for this type of modelling, reinforcing their potential for broader applications.

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REFERENCES

- Albouy, Y., Andrieux, P., Rakotondrasoa, G., Ritz, M., Descloitres, M., Join, J.-L., Rasolomanana, E., 2001. Mapping Coastal Aquifers by Joint Inversion of DC and TEM Soundings-Three Case Histories. *Groundwater* 39, 87–97. <https://doi.org/10.1111/j.1745-6584.2001.tb00354.x>
- Ali, J.R., Aitchison, J.C., 2005. Greater India. *Earth-Science Reviews* 72, 169–188. <https://doi.org/10.1016/j.earscirev.2005.07.005>
- Archie, G.E., 1942. The Electrical Resistivity Log as an Aid in Determining Some Reservoir Characteristics PETROLEUM TECHNOLOGY.
- Arps, J.J., 1953. The Effect of Temperature on the Density and Electrical Resistivity of Sodium Chloride Solutions. *Journal of Petroleum Technology* 5, 17–20. <https://doi.org/10.2118/953327-G>
- Auken, E., Boesen, T., Christiansen, A.V., 2017. A Review of Airborne Electromagnetic Methods With Focus on Geotechnical and Hydrological Applications From 2007 to 2017, in: *Advances in Geophysics*. Elsevier, pp. 47–93. <https://doi.org/10.1016/bs.agph.2017.10.002>
- Auken, E., Christiansen, A.V., 2004. Layered and laterally constrained 2D inversion of resistivity data. *GEOPHYSICS* 69, 752–761. <https://doi.org/10.1190/1.1759461>
- Auken, E., Christiansen, A.V., Jacobsen, L.H., Sørensen, K.I., 2008. A resolution study of buried valleys using laterally constrained inversion of TEM data. *Journal of Applied Geophysics* 65, 10–20. <https://doi.org/10.1016/j.jappgeo.2008.03.003>
- Auken, E., Christiansen, A.V., Kirkegaard, C., Andersen, K., Finadaca, G., Sørensen, K., Nyboe, N., 2015. An overview of the newest SkyTEM and inversion technologies with focus on resolution of shallow geological layers. Presented at the EAGE/DGG Workshop

on Airborne Geophysics 2015, Hannover, Germany. <https://doi.org/10.3997/2214-4609.201411989>

Auken, E., Christiansen, A.V., Kirkegaard, C., Fiandaca, G., Schamper, C., Behroozmand, A.A., Binley, A., Nielsen, E., Effersø, F., Christensen, N.B., Sørensen, K., Foged, N., Vignoli, G., 2014a. An overview of a highly versatile forward and stable inverse algorithm for airborne, ground-based and borehole electromagnetic and electric data. *Exploration Geophysics*, a 46, 223–235. <https://doi.org/10.1071/EG13097>

Auken, E., Foged, N., Larsen, J.J., Lassen, K.V.T., Maurya, P.K., Dath, S.M., Eiskjær, T.T., 2019. tTEM — A towed transient electromagnetic system for detailed 3D imaging of the top 70 m of the subsurface. *GEOPHYSICS* 84, E13–E22. <https://doi.org/10.1190/geo2018-0355.1>

Auken, E., Pellerin, L., Sørensen, K.I., 2001. Mutually constrained inversion (MCI) of electrical and electromagnetic data, in: SEG Technical Program Expanded Abstracts 2001. Presented at the SEG Technical Program Expanded Abstracts 2001, Society of Exploration Geophysicists, pp. 1455–1458. <https://doi.org/10.1190/1.1816378>

Beamish, D., Mattsson, A., 2003. Time-Lapse Airborne EM Surveys Across a Municipal Landfill. *JEEG* 8, 157–165. <https://doi.org/10.4133/JEEG8.3.157>

Berens, V., Hatch, M., Wilson, T., Hill, T., 2004. River-borne NanoTEM survey for location of salt accession to the River Murray at Loxton. *ASEG Extended Abstracts 2004*, 1–4. <https://doi.org/10.1071/ASEG2004ab010>

Bingemer, H.G., Crutzen, P.J., 1987. The production of methane from solid wastes. *J. Geophys. Res.* 92, 2181–2187. <https://doi.org/10.1029/JD092iD02p02181>

Binley, A., Kemna, A., 2005. DC Resistivity and Induced Polarization Methods, in: Rubin, Y., Hubbard, S.S. (Eds.), *Hydrogeophysics*, Water Science and Technology Library. Springer Netherlands, Dordrecht, pp. 129–156. https://doi.org/10.1007/1-4020-3102-5_5

Binley, A., Slater, L., 2020. Resistivity and induced polarization: Theory and applications to the near-surface earth. Cambridge University Press.

Binley, A., Winship, P., West, L.J., Pokar, M., Middleton, R., 2002. Seasonal variation of moisture content in unsaturated sandstone inferred from borehole radar and resistivity profiles. *Journal of Hydrology* 267, 160–172. [https://doi.org/10.1016/S0022-1694\(02\)00147-6](https://doi.org/10.1016/S0022-1694(02)00147-6)

Blanchy, G., Watts, Chris.W., Richards, J., Bussell, J., Huntenburg, K., Sparkes, D.L., Stalham, M., Hawkesford, M.J., Whalley, W.R., Binley, A., 2020. Time-lapse geophysical assessment of agricultural practices on soil moisture dynamics. *Vadose Zone Journal* 19, e20080. <https://doi.org/10.1002/vzj2.20080>

Boyd, J., Chambers, J., Wilkinson, P., Peppas, M., Watlet, A., Kirkham, M., Jones, L., Swift, R., Meldrum, P., Uhlemann, S., Binley, A., 2021. A linked geomorphological and geophysical modelling methodology applied to an active landslide. *Landslides* 18, 2689–2704. <https://doi.org/10.1007/s10346-021-01666-w>

Brown, C.M., 1989. Structural and stratigraphic framework of groundwater occurrence and surface discharge in the Murray Basin, southeastern Australia.

Brunet, P., Clément, R., Bouvier, C., 2010. Monitoring soil water content and deficit using Electrical Resistivity Tomography (ERT) – A case study in the Cevennes area, France. *Journal of Hydrology* 380, 146–153. <https://doi.org/10.1016/j.jhydrol.2009.10.032>

Cassiani, G., Boaga, J., Vanella, D., Perri, M.T., Consoli, S., 2015. Monitoring and modelling of soil–plant interactions: the joint use of ERT, sap flow and eddy covariance data to characterize the volume of an orange tree root zone. *Hydrol. Earth Syst. Sci.* 19, 2213–2225. <https://doi.org/10.5194/hess-19-2213-2015>

Cassiani, G., Godio, A., Stocco, S., Villa, A., Deiana, R., Frattini, P., Rossi, M., 2009. Monitoring the hydrologic behaviour of a mountain slope via time-lapse electrical resistivity tomography. *Near Surface Geophysics* 7, 475–486. <https://doi.org/10.3997/1873-0604.2009013>

Caterina, D., Flores Orozco, A., Nguyen, F., 2017. Long-term ERT monitoring of biogeochemical changes of an aged hydrocarbon contamination. *Journal of Contaminant Hydrology* 201, 19–29. <https://doi.org/10.1016/j.jconhyd.2017.04.003>

Chai, X., Tonjes, D.J., Mahajan, D., 2016. Methane emissions as energy reservoir: Context, scope, causes and mitigation strategies. *Progress in Energy and Combustion Science* 56, 33–70. <https://doi.org/10.1016/j.pecs.2016.05.001>

Chambers, J.E., Gunn, D.A., Wilkinson, P.B., Meldrum, P.I., Haslam, E., Holyoake, S., Kirkham, M., Kuras, O., Merritt, A., Wragg, J., 2014. 4D electrical resistivity tomography monitoring of soil moisture dynamics in an operational railway embankment. *Near Surface Geophysics* 12, 61–72. <https://doi.org/10.3997/1873-0604.2013002>

Chandra, S., Auken, E., Maurya, P.K., Ahmed, S., Verma, S.K., 2019. Large Scale Mapping of Fractures and Groundwater Pathways in Crystalline Hardrock By AEM. *Sci Rep* 9, 398. <https://doi.org/10.1038/s41598-018-36153-1>

Chandra, S., Tiwari, V.M., Vidyasagar, M., Raju, K.B., Choudhury, J., Lohithkumar, K., Nagaiah, E., Chandrapuri, S., Ahmed, S., Verma, S.K., 2021. Airborne Electromagnetic Signatures of an Ancient River in the Water-Stressed Ganga Plain, Prayagraj, India: A Potential Groundwater Repository. *Geophysical Research Letters* 48, e2021GL096100. <https://doi.org/10.1029/2021GL096100>

Christensen, N.B., 2022. Joint inversion of airborne TEM data and surface geoelectrical data. The Egebjerg case. *Journal of Applied Geophysics* 196, 104511. <https://doi.org/10.1016/j.jappgeo.2021.104511>

Christensen, N.B., 2000. Difficulties in determining electrical anisotropy in subsurface investigations. *Geophysical Prospecting*.

Christensen, N.K., Ferre, T.P.A., Fiandaca, G., Christensen, S., 2017. Voxel inversion of airborne electromagnetic data for improved groundwater model construction and prediction accuracy. *Hydrol. Earth Syst. Sci.* 21, 1321–1337. <https://doi.org/10.5194/hess-21-1321-2017>

Christensen, T.H., Kjeldsen, P., Albrechtsen, H., Heron, G., Nielsen, P.H., Bjerg, P.L., Holm, P.E., 1994. Attenuation of landfill leachate pollutants in aquifers. *Critical Reviews in Environmental Science and Technology* 24, 119–202. <https://doi.org/10.1080/10643389409388463>

Christiansen, A.V., Auken, E., Foged, N., Sørensen, K.I., 2007. Mutually and laterally constrained inversion of CVES and TEM data: a case study. *Near Surface Geophysics* 5, 115–123. <https://doi.org/10.3997/1873-0604.2006023>

Christiansen, A.V., Auken, E., Viezzoli, A., 2011. Quantification of modeling errors in airborne TEM caused by inaccurate system description. *GEOPHYSICS* 76, F43–F52. <https://doi.org/10.1190/1.3511354>

Cole, K.S., Cole, R.H., 1941. Dispersion and Absorption in Dielectrics I. Alternating Current Characteristics. *The Journal of Chemical Physics* 9, 341–351. <https://doi.org/10.1063/1.1750906>

Dahlin, T., Zhou, B., 2004. A numerical comparison of 2D resistivity imaging with 10 electrode arrays. *Geophysical Prospecting* 52, 379–398. <https://doi.org/10.1111/j.1365-2478.2004.00423.x>

Daily, W., Ramirez, A., LaBrecque, D., Nitao, J., 1992. Electrical resistivity tomography of vadose water movement. *Water Resources Research* 28, 1429–1442. <https://doi.org/10.1029/91WR03087>

Dalla Santa, G., Galgaro, A., Sassi, R., Cultrera, M., Scotton, P., Mueller, J., Bertermann, D., Mendrinós, D., Pasquali, R., Perego, R., Pera, S., Di Sipio, E., Cassiani, G., De Carli, M., Bernardi, A., 2020. An updated ground thermal properties database for GSHP applications. *Geothermics* 85, 101758. <https://doi.org/10.1016/j.geothermics.2019.101758>

Dauti, F., Viezzoli, A., Fiandaca, G., 2022. Induced Polarization Effects in Loupe Electromagnetic System 2022, 1–5. <https://doi.org/10.3997/2214-4609.202220185>

De Paola, F., Giugni, M., Pugliese, F., Annis, A., Nardi, F., 2018. GEV Parameter Estimation and Stationary vs. Non-Stationary Analysis of Extreme Rainfall in African Test Cities. *Hydrology* 5, 28. <https://doi.org/10.3390/hydrology5020028>

De Stefano, M., Golfré Andreasi, F., Re, S., Virgilio, M., Snyder, F.F., 2011. Multiple-domain, simultaneous joint inversion of geophysical data with application to subsalt imaging. *GEOPHYSICS* 76, R69–R80. <https://doi.org/10.1190/1.3554652>

De Vasconcelos, S.S., Batista, J.D.C., Leal, L.R.B., 2023. Multiple geophysical methods for mapping the geometry, leachate and biogas in old waste dumps in Northeast Brazil. <https://doi.org/10.21203/rs.3.rs-3340776/v1>

Descloitres, M., Ruiz, L., Sekhar, M., Legchenko, A., Braun, J., Mohan Kumar, M.S., Subramanian, S., 2008. Characterization of seasonal local recharge using electrical resistivity tomography and magnetic resonance sounding. *Hydrological Processes* 22, 384–394. <https://doi.org/10.1002/hyp.6608>

Doetsch, J., Linde, N., Vogt, T., Binley, A., Green, A.G., 2012. Imaging and quantifying salt-tracer transport in a riparian groundwater system by means of 3D ERT monitoring. *GEOPHYSICS* 77, B207–B218. <https://doi.org/10.1190/geo2012-0046.1>

Dumont, M., Reninger, P.A., Aunay, B., Pryet, A., Jougnot, D., Join, J.L., Michon, L., Martelet, G., 2021. Hydrogeophysical Characterization in a Volcanic Context From Local to Regional Scales Combining Airborne Electromagnetism and Magnetism. *Geophysical Research Letters* 48, e2020GL092000. <https://doi.org/10.1029/2020GL092000>

Effersø, F., Auken, E., Ingvard Sørensen, K., 1999. Inversion of band-limited TEM responses. *Geophysical Prospecting* 47, 551–564. <https://doi.org/10.1046/j.1365-2478.1999.00135.x>

Engelbrechtsen, K.W., Zhang, B., Fiandaca, G., Madsen, L.M., Auken, E., Christiansen, A.V., 2022. Accelerated 2.5-D inversion of airborne transient electromagnetic data using reduced 3-D meshing. *Geophysical Journal International* 230, 643–653. <https://doi.org/10.1093/gji/ggac077>

Farquharson, C.G., Oldenburg, D.W., 1998. Non-linear inversion using general measures of data misfit and model structure. *Geophysical Journal International* 134, 213–227. <https://doi.org/10.1046/j.1365-246x.1998.00555.x>

Fiandaca, G., Chen, J., Zhang, B., 2024. EEMverter, a New Modelling Tool for Electric and Electromagnetic Data with Focus on Induced Polarization, in: NSG 2024 30th European Meeting of Environmental and Engineering Geophysics. Presented at the NSG 2024 30th European Meeting of Environmental and Engineering Geophysics, European Association of Geoscientists & Engineers, Helsinki, Finland, pp. 1–5. <https://doi.org/10.3997/2214-4609.202420166>

Fiandaca, G., Christiansen, A.V., Auken, E., 2015. Depth of Investigation for Multi-parameters Inversions 2015, 1–5. <https://doi.org/10.3997/2214-4609.201413797>

Fiandaca, G., Dauti, F., Signora, A., 2022. Effect of Induced Polarization on Galvanic and Inductive Data: Where is it Stronger? 2022, 1–5. <https://doi.org/10.3997/2214-4609.202220193>

Fiandaca, Gianluca, Doetsch, J., Vignoli, G., Auken, E., 2015. Generalized focusing of time-lapse changes with applications to direct current and time-domain induced polarization inversions. *Geophysical Journal International* 203, 1101–1112. <https://doi.org/10.1093/gji/ggv350>

Fiandaca, G., Madsen, L.M., Maurya, P.K., 2018. Re-parameterisations of the Cole–Cole model for improved spectral inversion of induced polarization data. *Near Surface Geophysics* 16, 385–399. <https://doi.org/10.3997/1873-0604.2017065>

Fiandaca, G., Ramm, J., Binley, A., Gazoty, A., Christiansen, A.V., Auken, E., 2013. Resolving spectral information from time domain induced polarization data through 2-D inversion. *Geophysical Journal International* 192, 631–646. <https://doi.org/10.1093/gji/ggs060>

Fitterman, D.V., Anderson, W.L., 1987. Effect of transmitter turn-off time on transient soundings. *Geoexploration* 24, 131–146. [https://doi.org/10.1016/0016-7142\(87\)90087-1](https://doi.org/10.1016/0016-7142(87)90087-1)

Foged, N., Auken, E., Christiansen, A.V., Sørensen, K.I., 2013. Test-site calibration and validation of airborne and ground-based TEM systems. *GEOPHYSICS* 78, E95–E106. <https://doi.org/10.1190/geo2012-0244.1>

French, H., Binley, A., 2004. Snowmelt infiltration: monitoring temporal and spatial variability using time-lapse electrical resistivity. *Journal of Hydrology* 297, 174–186. <https://doi.org/10.1016/j.jhydrol.2004.04.005>

Gallardo, L.A., Meju, M.A., 2011. Structure-coupled multiphysics imaging in geophysical sciences. *Reviews of Geophysics* 49, 2010RG000330. <https://doi.org/10.1029/2010RG000330>

Gance, J., Malet, J.-P., Supper, R., Sailhac, P., Ottowitz, D., Jochum, B., 2016. Permanent electrical resistivity measurements for monitoring water circulation in clayey landslides. *Journal of Applied Geophysics* 126, 98–115. <https://doi.org/10.1016/j.jappgeo.2016.01.011>

Glendinning, S., Hughes, P., Helm, P., Chambers, J., Mendes, J., Gunn, D., Wilkinson, P., Uhlemann, S., 2014. Construction, management and maintenance of embankments used for road and rail infrastructure: implications of weather induced pore water pressures. *Acta Geotech.* 9, 799–816. <https://doi.org/10.1007/s11440-014-0324-1>

Glover, P.W.J., 2015. Geophysical Properties of the Near Surface Earth: Electrical Properties, in: *Treatise on Geophysics*. Elsevier, pp. 89–137. <https://doi.org/10.1016/B978-0-444-53802-4.00189-5>

Goebel, M., Knight, R., Halkjær, M., 2019. Mapping saltwater intrusion with an airborne electromagnetic method in the offshore coastal environment, Monterey Bay, California. *Journal of Hydrology: Regional Studies* 23, 100602. <https://doi.org/10.1016/j.ejrh.2019.100602>

Gorter, J., Hearty, D., Bond, A., 2004. Jurassic petroleum systems in the Houtman Sub-basin, northwestern offshore Perth Basin, Western Australia: a frontier petroleum province on the doorstep? *The APPEA Journal* 44, 13–58.

Gorter, J.D., Deighton, I., 2002. Effects of igneous activity in the offshore northern Perth Basin - evidence from petroleum exploration wells, 2D seismic and magnetic surveys.

Gunther, T., Rucker, C., n.d. A New Joint Inversion Approach Applied to the Combined Tomography of DC Resistivity and Seismic Refraction Data.

Haber, E., Holtzman Gazit, M., 2013. Model Fusion and Joint Inversion. *Surv Geophys* 34, 675–695. <https://doi.org/10.1007/s10712-013-9232-4>

Haber, E., Oldenburg, D., 1997. Joint inversion: a structural approach. *Inverse Problems* 13, 63–77. <https://doi.org/10.1088/0266-5611/13/1/006>

Hamilton-Smith, D.A., 2013. Salt mobilisation in a floodplain environment: using EM techniques to identify mechanisms that alter the distribution of saline groundwater.

Hatch, M., Munday, T., Heinson, G., 2010. A comparative study of in-river geophysical techniques to define variations in riverbed salt load and aid managing river salinization. *GEOPHYSICS* 75, WA135–WA147. <https://doi.org/10.1190/1.3475706>

Hayley, K., Bentley, L.R., Gharibi, M., 2009. Time-lapse electrical resistivity monitoring of salt-affected soil and groundwater. *Water Resources Research* 45, 2008WR007616. <https://doi.org/10.1029/2008WR007616>

Hayley, K., Bentley, L.R., Gharibi, M., Nightingale, M., 2007. Low temperature dependence of electrical resistivity: Implications for near surface geophysical monitoring. *Geophysical Research Letters* 34, 2007GL031124. <https://doi.org/10.1029/2007GL031124>

Hayley, K., Bentley, L.R., Pidlisecky, A., 2010. Compensating for temperature variations in time-lapse electrical resistivity difference imaging. *GEOPHYSICS* 75, WA51–WA59. <https://doi.org/10.1190/1.3478208>

Hayley, K., Pidlisecky, A., Bentley, L.R., 2011. Simultaneous time-lapse electrical resistivity inversion. *Journal of Applied Geophysics* 75, 401–411. <https://doi.org/10.1016/j.jappgeo.2011.06.035>

He, Z., Hu, Z., Gao, Y., He, L., Meng, C., Yang, L., 2015. Field test of monitoring gas reservoir development using time-lapse continuous electromagnetic profile method. *GEOPHYSICS* 80, WA127–WA134. <https://doi.org/10.1190/geo2014-0195.1>

- Hermans, T., Wildemeersch, S., Jamin, P., Orban, P., Brouyère, S., Dassargues, A., Nguyen, F., 2015. Quantitative temperature monitoring of a heat tracing experiment using cross-borehole ERT. *Geothermics* 53, 14–26. <https://doi.org/10.1016/j.geothermics.2014.03.013>
- Jodry, C., Palma Lopes, S., Fargier, Y., Sanchez, M., Côte, P., 2019. 2D-ERT monitoring of soil moisture seasonal behaviour in a river levee: A case study. *Journal of Applied Geophysics* 167, 140–151. <https://doi.org/10.1016/j.jappgeo.2019.05.008>
- Johansen, H.K., Sørensen, K., 1979a. FAST HANKEL TRANSFORMS*. *Geophysical Prospecting* 27, 876–901. <https://doi.org/10.1111/j.1365-2478.1979.tb01005.x>
- Johansen, H.K., Sørensen, K., 1979b. FAST HANKEL TRANSFORMS*. *Geophysical Prospecting* 27, 876–901. <https://doi.org/10.1111/j.1365-2478.1979.tb01005.x>
- Johansson, S., Fiandaca, G., Dahlin, T., 2015. Influence of non-aqueous phase liquid configuration on induced polarization parameters: Conceptual models applied to a time-domain field case study. *Journal of Applied Geophysics* 123, 295–309. <https://doi.org/10.1016/j.jappgeo.2015.08.010>
- Johnson, T.C., Versteeg, R.J., Day-Lewis, F.D., Major, W., Lane, J.W., 2015. Time-Lapse Electrical Geophysical Monitoring of Amendment-Based Biostimulation. *Groundwater* 53, 920–932. <https://doi.org/10.1111/gwat.12291>
- Jupp, D.L.B., Vozoff, K., 1977. RESOLVING ANISOTROPY IN LAYERED MEDIA BY JOINT INVERSION*. *Geophysical Prospecting* 25, 460–470. <https://doi.org/10.1111/j.1365-2478.1977.tb01181.x>
- Kang, S., Oldenburg, D.W., 2016. On recovering distributed IP information from inductive source time domain electromagnetic data. *Geophys. J. Int.* 207, 174–196. <https://doi.org/10.1093/gji/ggw256>
- Karaoulis, M., Revil, A., Werkema, D.D., Minsley, B.J., Woodruff, W.F., Kemna, A., 2011. Time-lapse three-dimensional inversion of complex conductivity data using an active time

constrained (ATC) approach: Time-lapse complex conductivity imaging. *Geophysical Journal International* 187, 237–251. <https://doi.org/10.1111/j.1365-246X.2011.05156.x>

Karaoulis, M.C., Kim, J.-H., Tsourlos, P.I., 2011. 4D active time constrained resistivity inversion. *Journal of Applied Geophysics* 73, 25–34. <https://doi.org/10.1016/j.jappgeo.2010.11.002>

Kim, J.-H., 2005. Four Dimensional Inversion of DC Resistivity Monitoring Data. <https://doi.org/10.3997/2214-4609-pdb.13.A006>

Kim, J.-H., Yi, M.-J., Park, S.-G., Kim, J.G., 2009. 4-D inversion of DC resistivity monitoring data acquired over a dynamically changing earth model. *Journal of Applied Geophysics* 68, 522–532. <https://doi.org/10.1016/j.jappgeo.2009.03.002>

Knight, R., Smith, R., Asch, T., Abraham, J., Cannia, J., Viezzoli, A., Fogg, G., 2018. Mapping Aquifer Systems with Airborne Electromagnetics in the Central Valley of California. *Groundwater* 56, 893–908. <https://doi.org/10.1111/gwat.12656>

LaBrecque, D.J., Ramirez, A.L., Daily, W.D., Binley, A.M., Schima, S.A., 1996. ERT monitoring of environmental remediation processes. *Meas. Sci. Technol.* 7, 375–383. <https://doi.org/10.1088/0957-0233/7/3/019>

LaBrecque, D.J., Yang, X., 2001. Difference Inversion of ERT Data: a Fast Inversion Method for 3-D In Situ Monitoring. *Journal of Environmental and Engineering Geophysics* 6, 83–89. <https://doi.org/10.4133/JEEG6.2.83>

Lane, R., Green, A., Golding, C., Owers, M., Pik, P., Plunkett, C., Sattel, D., Thorn, B., 2000. An example of 3D conductivity mapping using the TEMPEST airborne electromagnetic system. *Exploration Geophysics* 31, 162–172. <https://doi.org/10.1071/EG00162>

Lapenna, V., Perrone, A., 2022. Time-Lapse Electrical Resistivity Tomography (TL-ERT) for Landslide Monitoring: Recent Advances and Future Directions. *Applied Sciences* 12, 1425. <https://doi.org/10.3390/app12031425>

Last, B.J., Kubik, K., 1983. Compact gravity inversion. *GEOPHYSICS* 48, 713–721. <https://doi.org/10.1190/1.1441501>

Lavoué, F., Van Der Krak, J., Rings, J., André, F., Moghadas, D., Huisman, J.A., Lambot, S., Weiherrnüller, L., Vanderborght, J., Vereecken, H., 2010. Electromagnetic induction calibration using apparent electrical conductivity modelling based on electrical resistivity tomography. *Near Surface Geophysics* 8, 553–561. <https://doi.org/10.3997/1873-0604.2010037>

Lochbühler, T., Doetsch, J., Brauchler, R., Linde, N., 2013. Structure-coupled joint inversion of geophysical and hydrological data. *GEOPHYSICS* 78, ID1–ID14. <https://doi.org/10.1190/geo2012-0460.1>

Loke, M.H., Dahlin, T., Rucker, D.F., 2014. Smoothness-constrained time-lapse inversion of data from 3D resistivity surveys. *Near Surface Geophysics* 12, 5–24. <https://doi.org/10.3997/1873-0604.2013025>

Luo, Z., Guan, H., Zhang, X., 2019. The temperature effect and correction models for using electrical resistivity to estimate wood moisture variations. *Journal of Hydrology* 578, 124022. <https://doi.org/10.1016/j.jhydrol.2019.124022>

Madsen, L.M., Fiandaca, G., Auken, E., 2020. 3-D time-domain spectral inversion of resistivity and full-decay induced polarization data—full solution of Poisson’s equation and modelling of the current waveform. *Geophysical Journal International* 223, 2101–2116. <https://doi.org/10.1093/gji/ggaa443>

Marchant, D., Haber, E., Oldenburg, D.W., 2014. Three-dimensional modeling of IP effects in time-domain electromagnetic data. *GEOPHYSICS* 79, E303–E314. <https://doi.org/10.1190/geo2014-0060.1>

Matte, Ph., Mattauer, M., Olivet, J.M., Griot, D.A., 1997. Continental subductions beneath Tibet and the Himalayan orogeny: a review. *Terra Nova* 9, 264–270. <https://doi.org/10.1111/j.1365-3121.1997.tb00026.x>

Meju, M.A., 2005. Simple relative space–time scaling of electrical and electromagnetic depth sounding arrays: implications for electrical static shift removal and joint DC-TEM data inversion with the most-squares criterion. *Geophysical Prospecting* 53, 463–479. <https://doi.org/10.1111/j.1365-2478.2005.00483.x>

- Mendonça, C.A., Doherty, R., Amaral, N.D., McPolin, B., Larkin, M.J., Ustra, A., 2015. Resistivity and induced polarization monitoring of biogas combined with microbial ecology at a brownfield site. Interpretation 3, SAB43–SAB56. <https://doi.org/10.1190/INT-2015-0057.1>
- Miller, C.R., Routh, P.S., Brosten, T.R., McNamara, J.P., 2008. Application of time-lapse ERT imaging to watershed characterization. GEOPHYSICS 73, G7–G17. <https://doi.org/10.1190/1.2907156>
- Minsley, B.J., Rigby, J.R., James, S.R., Burton, B.L., Knierim, K.J., Pace, M.D.M., Bedrosian, P.A., Kress, W.H., 2021. Airborne geophysical surveys of the lower Mississippi Valley demonstrate system-scale mapping of subsurface architecture. Commun Earth Environ 2, 131. <https://doi.org/10.1038/s43247-021-00200-z>
- Modarres, R., 2007. Streamflow drought time series forecasting. Stoch Environ Res Ris Assess 21, 223–233. <https://doi.org/10.1007/s00477-006-0058-1>
- Monteiro Santos, F.A., Dupis, A., Andrade Afonso, A.R., Mendes Victor, L.A., 1997. 1D joint inversion of AMT and resistivity data acquired over a graben. Journal of Applied Geophysics 38, 115–129. [https://doi.org/10.1016/S0926-9851\(97\)80020-1](https://doi.org/10.1016/S0926-9851(97)80020-1)
- Moreira, C., Castro, M., Gonzalez, A., Cavallari, F., Munhoz, T., Pereira, A., 2014. Comparative Analysis between Biogas Flow in Landfill and Electrical Resistivity Tomography in Rio Claro City, Brazil. Journal of Geological Research 2014, 1–7. <https://doi.org/10.1155/2014/845906>
- Moreira, C.A., De Castro, M.C.A.A., Carrazza, L.P., Cavallari, F., Helene, L.P.I., Machado, F.B., 2015. RELATIONSHIP BETWEEN BIOGAS PRODUCTION AND VARIATIONS IN ELECTRIC RESISTIVITY IN LANDFILL OF RIO CLARO CITY, BRAZIL. Rev. Bras. Geof. 33. <https://doi.org/10.22564/rbgf.v33i2.715>
- Munday, T.J., Hill, A.J., Wilson, T., Hopkins, B., Telfer, A.L., White, G.J., Green, A., 2005. Combining geology and geophysics to develop a hydrogeologic framework for salt interception in the Loxton Sands aquifer, central Murray Basin, Australia. Australasian

Journal of Water Resources 9, 163–168.
<https://doi.org/10.1080/13241583.2005.11465274>

Musgrave, H., Binley, A., 2011. Revealing the temporal dynamics of subsurface temperature in a wetland using time-lapse geophysics. *Journal of Hydrology* 396, 258–266. <https://doi.org/10.1016/j.jhydrol.2010.11.008>

Nasta, P., Boaga, J., Deiana, R., Cassiani, G., Romano, N., 2019. Comparing ERT- and scaling-based approaches to parameterize soil hydraulic properties for spatially distributed model applications. *Advances in Water Resources* 126, 155–167. <https://doi.org/10.1016/j.advwatres.2019.02.014>

Norvick, M.S., 2003. Tectonic and Stratigraphic History of the Perth Basin. *Geoscience Australia, Record* 2004/16.

Oldenborger, G.A., Knoll, M.D., Routh, P.S., LaBrecque, D.J., 2007. Time-lapse ERT monitoring of an injection/withdrawal experiment in a shallow unconfined aquifer. *GEOPHYSICS* 72, F177–F187. <https://doi.org/10.1190/1.2734365>

Olsson, P.-I., Dahlin, T., Fiandaca, G., Auken, E., 2015. Measuring time-domain spectral induced polarization in the on-time: decreasing acquisition time and increasing signal-to-noise ratio. *Journal of Applied Geophysics* 123, 316–321. <https://doi.org/10.1016/j.jappgeo.2015.08.009>

Olsson, P.-I., Fiandaca, G., Larsen, J.J., Dahlin, T., Auken, E., 2016. Doubling the spectrum of time-domain induced polarization by harmonic de-noising, drift correction, spike removal, tapered gating and data uncertainty estimation. *Geophys. J. Int.* 207, 774–784. <https://doi.org/10.1093/gji/ggw260>

Palacios, A., Ledo, J.J., Linde, N., Luquot, L., Bellmunt, F., Folch, A., Marcuello, A., Queralt, P., Pezard, P.A., Martínez, L., Del Val, L., Bosch, D., Carrera, J., 2020. Time-lapse cross-hole electrical resistivity tomography (CHERT) for monitoring seawater intrusion dynamics in a Mediterranean aquifer. *Hydrol. Earth Syst. Sci.* 24, 2121–2139. <https://doi.org/10.5194/hess-24-2121-2020>

- Paz, M., Alcalá, F., Medeiros, A., Martínez-Pagán, P., Pérez-Cuevas, J., Ribeiro, L., 2020. Integrated MASW and ERT Imaging for Geological Definition of an Unconfined Alluvial Aquifer Sustaining a Coastal Groundwater-Dependent Ecosystem in Southwest Portugal. *Applied Sciences* 10, 5905. <https://doi.org/10.3390/app10175905>
- Pellicer, X.M., Zarroca, M., Gibson, P., 2012. Time-lapse resistivity analysis of Quaternary sediments in the Midlands of Ireland. *Journal of Applied Geophysics* 82, 46–58. <https://doi.org/10.1016/j.jappgeo.2012.02.009>
- Pelton, W.H., Rijo, L., Swift, C.M., 1978. INVERSION OF TWO-DIMENSIONAL RESISTIVITY AND INDUCED-POLARIZATION DATA. *GEOPHYSICS* 43, 788–803. <https://doi.org/10.1190/1.1440854>
- Portniaguine, O., Zhdanov, M.S., 1999. Focusing geophysical inversion images. *GEOPHYSICS* 64, 874–887. <https://doi.org/10.1190/1.1444596>
- Quaife, P., Rosser, J., Pagnozzi, S., 1994. The structural architecture and stratigraphy of the offshore northern Perth Basin, Western Australia.
- Raiche, A.P., Jupp, D.L.B., Rutter, H., Vozoff, K., 1985. The joint use of coincident loop transient electromagnetic and Schlumberger sounding to resolve layered structures. *GEOPHYSICS* 50, 1618–1627. <https://doi.org/10.1190/1.1441851>
- Ramirez, A., Daily, W., LaBrecque, D., Owen, E., Chesnut, D., 1993. Monitoring an underground steam injection process using electrical resistance tomography. *Water Resources Research* 29, 73–87. <https://doi.org/10.1029/92WR01608>
- Rao, S., Lesparre, N., Flores-Orozco, A., Wagner, F., Kemna, A., Javaux, M., 2020. Imaging plant responses to water deficit using electrical resistivity tomography. *Plant Soil* 454, 261–281. <https://doi.org/10.1007/s11104-020-04653-7>
- Rein, A., Hoffmann, R., Dietrich, P., 2004. Influence of natural time-dependent variations of electrical conductivity on DC resistivity measurements. *Journal of Hydrology* 285, 215–232. <https://doi.org/10.1016/j.jhydrol.2003.08.015>

Revil, A., 2012. Spectral induced polarization of shaly sands: Influence of the electrical double layer. *Water Resources Research* 48, 2011WR011260. <https://doi.org/10.1029/2011WR011260>

Roberts, J.J., 2002. Electrical properties of microporous rock as a function of saturation and temperature. *Journal of Applied Physics* 91, 1687–1694. <https://doi.org/10.1063/1.1430544>

Römhild, L., Fiandaca, G., Hu, L., Meyer, L., Bayer, P., 2022. Imaging hydraulic conductivity in near-surface aquifers by complementing cross-borehole induced polarization with hydraulic experiments. *Advances in Water Resources* 170, 104322. <https://doi.org/10.1016/j.advwatres.2022.104322>

SA Water, 2018. River Murray Daily Flow data.

Sandberg, S.K., 1993. EXAMPLES OF RESOLUTION IMPROVEMENT IN GEOELECTRICAL SOUNDINGS APPLIED TO GROUNDWATER INVESTIGATIONS¹. *Geophysical Prospecting* 41, 207–227. <https://doi.org/10.1111/j.1365-2478.1993.tb00866.x>

Sandersen, P.B.E., Kallesøe, A.J., Møller, I., Høyer, A.-S., Jørgensen, F., Pedersen, J.B., Christiansen, A.V., 2021. Utilizing the towed Transient ElectroMagnetic method (tTEM) for achieving unprecedented near-surface detail in geological mapping. *Engineering Geology* 288, 106125. <https://doi.org/10.1016/j.enggeo.2021.106125>

Santos Monteiro, F.A., El-Kaliouby, H.M., 2010. Comparative study of local versus global methods for 1D joint inversion of direct current resistivity and time-domain electromagnetic data. *Near Surface Geophysics* 8, 135–143. <https://doi.org/10.3997/1873-0604.2009056>

Sapia, V., Viezzoli, A., Oldenborger, G., 2015. Joining multiple AEM datasets to improve accuracy, cross calibration and derived products: The Spiritwood VTEM and AeroTEM case study. *Near Surface Geophysics* 13, 61–72. <https://doi.org/10.3997/1873-0604.2014041>

Seigel, H.O., 1959. MATHEMATICAL FORMULATION AND TYPE CURVES FOR INDUCED POLARIZATION. GEOPHYSICS 24, 547–565. <https://doi.org/10.1190/1.1438625>

Sen, P.N., Goode, P.A., 1992. Influence of temperature on electrical conductivity on shaly sands. GEOPHYSICS 57, 89–96. <https://doi.org/10.1190/1.1443191>

Sherrod, L., Sauck, W., Werkema, D.D., 2012. A Low-Cost, In Situ Resistivity and Temperature Monitoring System. Groundwater Monitoring Rem 32, 31–39. <https://doi.org/10.1111/j.1745-6592.2011.01380.x>

Signora, A., 2025a. Time Lapse Airborne EM for monitoring the evolution of a saltwater aquifer - The Bookpurnong case study. <https://doi.org/10.5281/zenodo.14826900>

Signora, A., 2025b. Time Lapse Airborne EM for monitoring the evolution of a saltwater aquifer - The Bookpurnong case study (video b). <https://doi.org/10.5281/zenodo.14826971>

Signora, A., 2025c. Time Lapse Airborne EM for monitoring the evolution of a saltwater aquifer - The Bookpurnong case study (video c). <https://doi.org/10.5281/zenodo.14827081>

Signora, A., Galli, S., Gisolo, M., Fiandaca, G., 2023. The HydroGeosITe for AEM mapping: characterization through joint inversion of AEM, ground EM and DCIP data. Presented at the 8th International Airborne Electromagnetics Workshop, Zenodo, Fitzroy Island, Queensland, Australia. <https://doi.org/10.5281/zenodo.10067884>

Singh, V.P., 1998. Entropy-Based Parameter Estimation in Hydrology, Water Science and Technology Library. Springer Netherlands, Dordrecht. <https://doi.org/10.1007/978-94-017-1431-0>

Singha, K., Day-Lewis, F.D., Johnson, T., Slater, L.D., 2015. Advances in interpretation of subsurface processes with time-lapse electrical imaging. Hydrological Processes 29, 1549–1576. <https://doi.org/10.1002/hyp.10280>

Smith, R.S., West, G.F., 1988. Inductive interaction between polarizable conductors: An explanation of a negative coincident-loop transient electromagnetic response. *GEOPHYSICS* 53, 677–690. <https://doi.org/10.1190/1.1442502>

Sorensen, K.I., Auken, E., 2004. SkyTEM—a New High-resolution Helicopter Transient Electromagnetic System. *Exploration Geophysics* 35, 194–202. <https://doi.org/10.1071/EG04194>

Steelman, C.M., Kennedy, C.S., Capes, D.C., Parker, B.L., 2017. Electrical resistivity dynamics beneath a fractured sedimentary bedrock riverbed in response to temperature and groundwater–surface water exchange. *Hydrol. Earth Syst. Sci.* 21, 3105–3123. <https://doi.org/10.5194/hess-21-3105-2017>

Sullivan, N.A.L., Gisolo, M., Spagnoli, L., Rapiti, A., Dauti, F., Menghini, A., Viezzoli, A., Fiandaca, G., 2023. Airborne EM in northern Italy for sustainable and resilient management of groundwater resources. *Il Nuovo Cimento C* 46, 1–11. <https://doi.org/10.1393/ncc/i2023-23068-y>

Sullivan, N.A.L., Viezzoli, A., Fiandaca, G., 2024. EEMstudio: Process and Model Electric and Electromagnetic Data with a QGIS Plugin 2024, 1–5. <https://doi.org/10.3997/2214-4609.202420154>

Sundberg, K., 1932. Effect Of Impregnating Waters On Electrical Conductivity Of Soils And Rocks*. *The Log Analyst* 21.

Symonds, P.A., Planke, S., Frey, O., Skogseid, J., 1998. Volcanic evolution of the Western Australian continental margin and its implications for basin development.

Telfer, A.L., Berens, V., Hatch, M., Palfreyman, C., 2005. Instream NanoTEM: providing increased resolution to stream salinisation and floodplain processes along the River Murray, southeast Australia. *Australasian Journal of Water Resources* 9, 155–161. <https://doi.org/10.1080/13241583.2005.11465273>

Themelis, N.J., Ulloa, P.A., 2007. Methane generation in landfills. *Renewable Energy* 32, 1243–1257. <https://doi.org/10.1016/j.renene.2006.04.020>

- Tijdeman, E., Stahl, K., Tallaksen, L.M., 2020. Drought Characteristics Derived Based on the Standardized Streamflow Index: A Large Sample Comparison for Parametric and Nonparametric Methods. *Water Resources Research* 56, e2019WR026315. <https://doi.org/10.1029/2019WR026315>
- Tildy, P., Neduczai, B., Nagy, P., Kanli, A.I., Hegymegi, C., 2017. Time lapse 3D geoelectric measurements for monitoring of in-situ remediation. *Journal of Applied Geophysics* 136, 99–113. <https://doi.org/10.1016/j.jappgeo.2016.10.037>
- Van Voorhis, G.D., Nelson, P.H., Drake, T.L., 1973. Complex resistivity spectra of porphyry copper mineralization. *Geophysics* 38, 49–60. <https://doi.org/10.1190/1.1440333>
- Vest Christiansen, A., Auken, E., 2012. A global measure for depth of investigation. *GEOPHYSICS* 77, WB171–WB177. <https://doi.org/10.1190/geo2011-0393.1>
- Viezzoli, A., Auken, E., Munday, T., 2009. Spatially constrained inversion for quasi 3D modelling of airborne electromagnetic data – an application for environmental assessment in the Lower Murray Region of South Australia. *Exploration Geophysics* 40, 173–183. <https://doi.org/10.1071/EG08027>
- Viezzoli, A., Christiansen, A.V., Auken, E., Sørensen, K., 2008. Quasi-3D modeling of airborne TEM data by spatially constrained inversion. *GEOPHYSICS* 73, F105–F113. <https://doi.org/10.1190/1.2895521>
- Viezzoli, A., Dauti, F., Mule, S., Munday, T., Brodie, R., Fiandaca, G., Farinelli, S., 2024. Modelling IP in Tempest data: the first preliminary steps and insights. Presented at the ASEG DISCOVER Symposium (ASEG), Zenodo, Hobart, Australia. <https://doi.org/10.5281/zenodo.13918379>
- Viezzoli, A., Jørgensen, F., Sørensen, C., 2013. Flawed Processing of Airborne EM Data Affecting Hydrogeological Interpretation. *Groundwater* 51, 191–202. <https://doi.org/10.1111/j.1745-6584.2012.00958.x>

- Viezzoli, A., Manca, G., 2020. On airborne IP effects in standard AEM systems: tightening model space with data space. *Exploration Geophysics* 51, 155–169. <https://doi.org/10.1080/08123985.2019.1681895>
- Viezzoli, A., Munday, T., Auken, E., Christiansen, A.V., Wilson, G.A., 2010. Accurate quasi 3D versus practical full 3D inversion of AEM data – the Bookpurnong case study. *Preview* 2010, 23–31. <https://doi.org/10.1071/PVv2010n149p23>
- Vonk, M.A., 2024. SPEI: A simple Python package to calculate and visualize drought indices. <https://doi.org/10.5281/zenodo.10816741>
- Vozoff, K., Jupp, D.L.B., 2007. Joint Inversion of Geophysical Data. *Geophysical Journal of the Royal Astronomical Society* 42, 977–991. <https://doi.org/10.1111/j.1365-246X.1975.tb06462.x>
- Ward, S.H., Hohmann, G.W., 1988. *Electromagnetic Methods in Applied Geophysics: Volume 1, Theory*. Society of Exploration Geophysicists. <https://doi.org/10.1190/1.9781560802631>
- Waxman, M.H., Thomas, E.C., 1972. Electrical Conductivities in Shaly Sands - I. The Relation Between Hydrocarbon Saturation and Resistivity Index; II. The Temperature Coefficient of Electrical Conductivity. Presented at the Fall Meeting of the Society of Petroleum Engineers of AIME, p. SPE-4094-MS. <https://doi.org/10.2118/4094-MS>
- Weller, A., Seichter, M., Kampke, A., 1996. Induced-polarization modelling using complex electrical conductivities. *Geophysical Journal International* 127, 387–398. <https://doi.org/10.1111/j.1365-246X.1996.tb04728.x>
- Weller, A., Slater, L., Binley, A., Nordsiek, S., Xu, S., 2015. Permeability prediction based on induced polarization: Insights from measurements on sandstone and unconsolidated samples spanning a wide permeability range. *GEOPHYSICS* 80, D161–D173. <https://doi.org/10.1190/geo2014-0368.1>

Weller, A., Slater, L., Nordsiek, S., 2013. On the relationship between induced polarization and surface conductivity: Implications for petrophysical interpretation of electrical measurements. *GEOPHYSICS* 78, D315–D325. <https://doi.org/10.1190/geo2013-0076.1>

Wyllie, M.R.J., Rose, W.D., 1950. Some Theoretical Considerations Related To The Quantitative Evaluation Of The Physical Characteristics Of Reservoir Rock From Electrical Log Data. *Journal of Petroleum Technology* 2, 105–118. <https://doi.org/10.2118/950105-G>

Xiao, L., Fiandaca, G., Maurya, P.K., Christiansen, A.V., Lévy, L., 2022a. Three-dimensional time-lapse inversion of transient electromagnetic data, with application at an Icelandic geothermal site. *Geophysical Journal International*, b 231, 584–596. <https://doi.org/10.1093/gji/ggac206>

Xiao, L., Fiandaca, G., Zhang, B., Auken, E., Christiansen, A.V., 2022b. Fast 2.5D and 3D inversion of transient electromagnetic surveys using the octree-based finite-element method. *GEOPHYSICS*, a 87, E267–E277. <https://doi.org/10.1190/geo2021-0402.1>

Yan, W., Howles, S., Howe, B., Hill, T., 2005. Loxton – Bookpurnong Numerical Groundwater Model 2005.

Yan, W., Li, C., Woods, J., 2011. Loxton-Bookpurnong numerical groundwater model 2011. Volume 1, Report and figures. Science, Monitoring and Information Division, Department for Water, Adelaide.

Yi, M.-J., Sasaki, Y., 2015. 2-D and 3-D joint inversion of loop–loop electromagnetic and electrical data for resistivity and magnetic susceptibility. *Geophys. J. Int.* 203, 1085–1095. <https://doi.org/10.1093/gji/ggv354>

Zhang, B., Engebretsen, K.W., Fiandaca, G., Cai, H., Auken, E., 2021. 3D inversion of time-domain electromagnetic data using finite elements and a triple mesh formulation. *GEOPHYSICS* 86, E257–E267. <https://doi.org/10.1190/geo2020-0079.1>

