Lawrence Berkeley National Laboratory

Recent Work

Title

Decay curve analysis for data error quantification in time-domain induced polarization imaging

Permalink

<https://escholarship.org/uc/item/3qf2z4tb>

Journal

Geophysics, 83(2)

ISSN

0016-8033

Authors

Flores Orozco, A
Gallistl, J
Bücker, M
et al.

Publication Date

2018-03-01

DOI

10.1190/geo2016-0714.1

Peer reviewed

Decay curve analysis for data error quantification in time-domain induced polarization imaging

Adrian Flores Orozco¹, Jakob Gallistl¹, Matthias Buecker² and Kenneth H. Williams³

¹TU-Wien, Geophysics Research Group, Department of Geodesy and Geoinformation, Vienna, Austria. E-mail: flores@tuwien.ac.at; adrian.flores-orozco@geo.tuwien.ac.at; jakob.gallistl@geo.tuwien.ac.at.

²TU-Wien, Geophysics Research Group, Department of Geodesy and Geoinformation, Vienna, Austria and University of Bonn, Department of Geophysics, Steinmann Institute, Bonn, Germany. E-mail: buecker@geo.uni-bonn.de.

³Lawrence Berkeley National Laboratory, Earth Sciences Division, Berkeley, California, USA. E-mail: khwilliams@lbl.gov.

Abstract

In recent years, the time-domain induced polarization (TDIP) imaging technique has emerged as a suitable method for the characterization and the monitoring of hydrogeologic and biogeochemical processes. However, one of the major challenges refers to the resolution of the electrical images. Hence, various studies have stressed the importance of data processing, error characterization, and the deployment of adequate inversion schemes. A widely accepted method to assess data error in electrical imaging relies on the analysis of the discrepancy between normal and reciprocal measurements. Nevertheless, the collection of reciprocals doubles the acquisition time and is only viable for a limited subset of commonly used electrode configurations (e.g., dipole-dipole [DD]). To overcome these limitations, we have developed a new methodology to quantify the data error in TDIP imaging, which is entirely based on the analysis of the recorded IP decay curve and does not require recollection of data (e.g., reciprocals). The first two steps of the methodology assess the general characteristics of the decay curves and the spatial consistency of the measurements for the detection and removal of outliers. In the third and fourth steps, we quantify the deviation of the measured decay curves from a smooth model for the estimation of random error of the total chargeability and transfer resistance measurement. The error models and imaging results obtained from this methodology — in the following referred to as “decay curve analysis” — are compared with those obtained following a conventional normal-reciprocal analysis revealing consistent results. We determine the applicability of our methodology with real field data collected at the floodplain scale (approximately 12 ha) using multiple gradient and DD configurations.

Keywords: induced polarization, IP data processing, error quantification, time-domain IP, electrical imaging, near-surface exploration

Introduction

Initially developed for the prospection of metallic ores, the induced polarization (IP) method has emerged in recent years as a suitable technique for environmental and hydrogeologic studies. As an extension of the standard DC-resistivity method, IP measurements provide information about the electrical conductivity (i.e., energy loss) and capacitive (i.e., energy storage) properties of the subsurface permitting an improved lithologic characterization (Kemna et al., 2012; Weller et al., 2013). Particularly at the field scale, time-domain IP (TDIP) measurements have become popular within the past few years due to the robustness and accuracy of modern commercial measuring devices. An increasing number of studies report meaningful TDIP imaging results for a wide range of applications, such as the characterization of contaminated sites (Flores Orozco et al., 2012a; Gazoty et al., 2012), the assessment of seasonal changes in permafrost (Doetsch et al., 2015a), the evaluation of processes associated with CO₂ injections to shallow aquifers (Dafflon et al., 2012; Doetsch et al., 2015b), and the monitoring of zero-valent iron nanoparticles injections (Flores Orozco et al., 2015). Furthermore, a recent study has described the prospection of microbial “hot spots” at the floodplain scale using TDIP imaging (Wainwright et al., 2015), demonstrating the applicability of the TDIP method for exploration at large scale (the floodplain covered approximately 12 ha). If based only on the analysis of soil and groundwater samples, floodplain-scale site characterization suffers from the limitations imposed by the characteristics of the sampling and often lacks the spatial resolution needed to identify small heterogeneities such as microbial hot spots. The ability of the TDIP imaging method to gain quasi-continuous information about textural and geochemical properties of soil materials makes it an attractive technique for hydrogeologic investigations (Binley et al., 2016); in addition, the characteristic polarization response associated to biomass (e.g., microbial cells) and related metabolic products has been exploited for innovative applications in the emerging field of biogeophysics (Atekwana and Slater, 2009; Kemna et al., 2012). However, as pointed out by Wainwright et al. (2015), the modest polarization response of soil materials with low (to negligible) metallic content places high demands on the resolution of the IP imaging results.

An adequate characterization of the data error is critical to enhance the resolution of electrical images, considering that an underestimation of data error is typically associated to the creation of artifacts in the images, whereas data error overestimation generally leads to the loss of resolution (LaBrecque et al., 1996). Data errors can be systematic or random; the main source for systematic errors in electrical imaging measurements is due to poor contact between the electrodes and the ground, resulting in low current injections and noisy voltage readings. In addition, TDIP measurements are subject to other sources of systematic error due to (1) electromagnetic capacitive and inductive coupling, which affects potential readings collected in the early times (e.g., Dahlin and Leroux, 2012), and (2) distortions in

potential measurements performed by electrodes placed within the current pathway or previously used for current injection, due to a (remnant) polarization of the electrode itself (e.g., Dahlin et al., 2002). Measurements affected by systematic error need to be removed as outliers before the inversion. To this end, a recent study proposed the analysis of TDIP data collected at high sampling rates (3.75 kHz) to reduce the effect due to the drift and polarization of the electrodes, spikes in the voltage readings, or harmonic noise due to AC power supplies (Olsson et al., 2016). Remaining uncertainties in the data can be considered random error, related to variations in magnitude and pathways of the injected current, electronic noise of the measuring instrument, etc., and they can generally be roughly described by the mean and standard deviation (e.g., Binley et al., 1995; LaBrecque et al., 1996; Slater et al., 2000). It has been widely documented that inversion algorithms minimizing an objective function subject to fitting the data to a predefined error level (given by the estimates of random error) might provide results less affected by artifacts than those computed by strictly minimizing the data misfit (e.g., Binley et al., 1995; LaBrecque et al., 1996; Kemna, 2000). Field studies have confirmed the advantages of accurately incorporating information about the data error for the inversion of TDIP imaging data sets (e.g., Slater and Binley, 2006; Kemna et al., 2012; Flores Orozco et al., 2015; Binley et al., 2016). Flores Orozco et al. (2012b) recently adopted a power-law model to characterize the data error in IP measurements (i.e., phase or chargeability) as a function of the associated transfer resistance, yielding imaging results with an improved resolution over those computed using previous assumptions of a constant error.

Therefore, during the processing of the data, quantitative information on the characteristics of data error is required to (1) assess the reliability of the data, (2) identify and remove outliers associated with systematic errors, and (3) adjust error models describing the characteristics of inherent random errors to be incorporated within the inversion. Besides error quantification for data inversion, the characterization of large areas by means of IP imaging demands an onsite assessment of data quality to (1) eventually indicate the need to increase the signal-to-noise ratio (S/N), e.g., by modifying the measuring protocol and (2) determine areas of interest for the collection of denser data sets (e.g., higher resolution). To date, a widely used method to evaluate IP data quality is based on the analysis of the misfit between normal and reciprocal measurements, in which reciprocal measurements refer to the recollection of the data with interchanged current and potential electrodes (e.g., Slater et al., 2000; Slater and Binley, 2006; Flores Orozco et al., 2011, 2012a, 2012b). Nevertheless, the necessity to reduce the acquisition time for large-scale surveys compromises the collection of reciprocals. Furthermore, measuring configurations characterized by high S/N, such as the multiple-gradient (MG) array (Dahlin and Zhou, 2006), are not suited for the collection of reciprocals with multichannel instruments without

severely increasing the acquisition time. Accordingly, IP surveys at the large scale urge for the development of new techniques to quickly and reliably quantify data error without the need of reciprocal readings.

Here, we propose a new methodology for the processing of TDIP measurements based on the analysis of the voltage decay curve. Our decay curve analysis (DCA) permits us to identify and remove outliers prior to the inversion, and it is also suited to quantify data error in TDIP imaging measurements. To evaluate the accuracy of our approach, we compare its outcome with the one obtained from the widely used normal-reciprocal analysis (NRA). We further demonstrate the robustness and efficiency of the proposed DCA by applying it to an extensive TDIP data set collected at the floodplain scale (approximately 12 ha) for the characterization of a near-surface aquifer and the identification of possible naturally reduced zones (NRZ) associated to microbial hot spots in the aquifer sediments. In the following section, we will briefly describe the characteristics of the site and the field measurements, as well as the algorithm used for the inversion of the TDIP data; this is followed by the step-by-step description of our DCA. Then, we present the electrical imaging results as obtained by means of the DCA and the comparison with those obtained by the standard NRA, followed by the discussion and conclusions.

Materials and Methods

Site description and TDIP survey

TDIP measurements were collected on the Shiprock site (New Mexico, USA) on the grounds of a former uranium-processing facility. The site has been remediated, but measurable concentrations of uranium are still present in groundwater samples. The affected floodplain of the San Juan River has a total extension of approximately 45 ha, and its stratigraphy consists of three main units: an impermeable clay-rich layer extending from the surface to approximately 2 m depth, followed by a sandy-gravel aquifer (approximately 3 m thickness) that rests on top of a shale unit of low hydraulic permeability known as the Mancos Shale formation. The groundwater level was located at a depth of approximately 3 m during the field survey. A previous study on a similar site (Wainwright et al., 2015) revealed that fluvially deposited organic material within aquifer sediments may result in the development of microbial hotspots, consequently leading to the natural immobilization of uranium and the accumulation of reduced end products, such as biominerals (e.g., iron monosulfides, FeS) and pore fluids (e.g., methane and carbon dioxide). To map possible hot spots at the Shiprock site, a total of 22 TDIP profiles were collected (Figure 1). Six roll-along profiles (up to 350 m) were laid out to characterize large-scale changes in the electrical properties across the active margin of the floodplain (approximately 12 ha), with 16 shorter profiles included to improve the resolution of particular areas of interest. Separation between electrodes was 2 m for all profiles for an intended depth of investigation of 7 m, which fairly covers the aquifer and the contact to the

Mancos Shale. Measurements were collected using the Syscal Pro Switch 72 equipment (from IRIS Instruments) with a square-wave current injection, 50% duty cycle, and a pulse length of 2 s. The voltage decay was measured along 20 windows using an arithmetic distribution of the IP windows, i.e., having the same duration of 80 ms and starting after an initial delay of 240 ms after current shutoff. Such settings were chosen as a trade-off between acquisition time (favored by a short pulse length) and the response due to slow polarization processes (favored by long pulse lengths), a fair sampling of the decay curve (for early and late times), and an ample delay to minimize the electromagnetic coupling in the data. Furthermore, data collected with the same settings yielded good results for the delineation of microbial hot spots at a site with similar characteristics (Wainwright et al., 2015). Measurements were collected using two configurations: (1) dipole-dipole (DD) skip 0 (i.e., a length of 2 m for the current and potential dipoles) and (2) MG configurations (after Dahlin and Zhou, 2006) with 10 potential dipoles (skip 0, skip 1, and skip 2) nested within the current dipole. DD measurements were collected as normal-reciprocal pairs. All data sets were inverted with CRTomo, a smoothness-constraint algorithm (by Kemna, 2000) that permits the inversion of the data to a confidence level determined by an error model. The algorithm calculates the complex resistivity distribution on a 2D grid of lumped finite element cells from a given data set of transfer impedances, in terms of magnitude and phase, at a given frequency (for further details, we refer to Kemna, 2000). Modeling errors in CRTomo have been estimated at less than 2% (Weigand et al., 2017). To compute the phase shift of the electrical impedance, apparent total chargeability values were linearly converted to frequency-domain phase values (at the fundamental frequency of 0.125 Hz) assuming a constant-phase response (van Voorhis et al., 1973), based on the approach proposed by Kemna et al. (1999). This approach demonstrated quantitatively consistent results obtained from time- and frequency-domain data sets (Flores Orozco et al., 2012a).

Figure 1. Layout of the geophysical survey at the Shiprock study area. The white lines indicate TDIP profiles, the yellow line highlights the first section (64 electrodes) of profile 1 used as an exemplary data set for the application of the DCA method. Satellite image modified from Google Earth.

Data processing

Figure 2 illustrates typical manifestations of errors observed in TDIP data sets: Measurements collected with a small separation between current and

potential electrodes (high S/N) are typically related to smoothly decaying curves (Figure 2a), whereas increasing the separation between the potential and current electrodes (Figure 2b and 2c) is associated with more erratic curves due to a decrease in the S/N. Although shape and magnitude of most decay curves are similar, some measurements clearly deviate from the general “decay” pattern, with voltage increasing after current shutoff (e.g., Figure 2d). These outliers are commonly a result of capacitive coupling (Dahlin and Loke, 2015) and need to be deleted before the inversion of the data.

Figure 2. Plots of the measured decay curves with DD configurations (black symbols) for (a) small, (b) medium and (c and d) maximum separation between current and potential dipoles (i.e., representing different S/Ns). The negative power law model (after equation 2) fitted to each curve is indicated with the red line.

The effects of systematic and random error on TDIP decay curves have been recognized earlier and previous studies proposed to manually remove measurements associated with an erratic behavior of the decay curves (Gazoty et al., 2013; Doetsch et al., 2015a; 2015b). However, an approach that relies on the manual identification of outliers is not suited for the processing of extensive data sets, which calls for automatable filtering schemes. Gazoty et al. (2013) and Olsson et al. (2015) suggest statistical analysis of repeated measurements (i.e., stacking) to remove outliers and the quantification of data error. Yet repeatability is not well-suited to reduce the acquisition time and does not offer any advantage in comparison with NRA (LaBrecque et al., 1996). Moreover, the existing approaches do not offer the possibility to quantify the random error on the TDIP measurements. This is particularly important for the inversion of measurements collected with large dipole separations, which typically suffer from a low S/N and cannot just be removed as outliers, considering that the information from these measurements is critical to improve the quantitative interpretation of electrical images at depth. Instead of eliminating curves with an erratic behavior, we propose to perform an adequate quantification of the error in the measured decay curves (i.e., deviating from a smooth decay curve) and incorporate such information into the inversion as part of the error model. Furthermore, systematic errors in the data may lead to measurements related to a smooth decay curve but associated to total chargeability values without spatial correlation within the data set, i.e., values inconsistent with measurements collected with neighbor electrodes. Such measurements also

need to be removed before the inversion. Thus, analysis of TDIP data sets requires the assessment of the quality of the decay curve (for the quantification of random error) and the spatial correlation of the measurements within the TDIP imaging data set (for the identification of systematic errors).

In the following section, we describe a novel four-step methodology that provides an improved and automatable outlier removal as well as an adequate quantification of data error for the transfer resistance and the total chargeability measurement. By transfer resistance, we mean the ratio of the measured primary voltage to the injected current ($R=U/I$) and by apparent total chargeability the normalized sum of NN individual chargeabilities m_i times the respective durations Δt_i of NN IP windows (Binley and Kemna, 2005):

$$M = \frac{\sum_{i=1}^N (m_i \cdot \Delta t_i)}{\sum_{i=1}^N \Delta t_i} \quad (1)$$

Note that much of the erratic variation of the decay curves observed in Figure 2 is averaged out by the calculation of the total chargeability MM as the temporal average of the voltage decay (equation 1). The main idea of our methodology is to reconstruct the standard deviation of this average by comparing the measured decay curve with a representative smooth decay. This estimated standard deviation of the apparent chargeability can then be used to adjust the error model required for the inversion.

DECAY CURVE ANALYSIS

Power-law fit and first filter

The first step consists of fitting an approximate power-law model to each of the measured decay curves, for each profile:

$$m_f(t) = \alpha t^{-\beta} + \epsilon. \quad (2)$$

Here, m_f represents the fitted apparent chargeability (in mV/VmV/V), t represents the time (in ms) after current shutoff, and α and β are the fitting parameters. We also include a constant term ϵ to account for deviations from a pure power law. Power-law models are well-suited to describe most TDIP responses and can be considered the time domain equivalent of the frequency-domain constant-phase model (van Voorhis et al., 1973). As can be observed in Figure 2, the power-law model yields a fair and robust fit of most decays in the sample data set. To assess the goodness of each fit, we calculate the root-mean-square deviation (rmsd) between the measured and fitted curves as

$$\text{rmsd} = \sqrt{\frac{1}{N} \sum_{i=1}^N (m_f(t_i) - m_{m,i})^2}, \quad (3)$$

where NN is the number of IP windows of the curve and $m_{m,i}$ are the apparent chargeabilities at times t_i .

Considering that physically meaningful measured decay curves should be positive and decrease with time, we remove all measurements associated with nondecaying curves ($\beta < 0$ and $\alpha < 0$, or $\beta > 0$ and $\alpha > 0$). The incorporation of the so-called negative IP effect (e.g., Dahlin and Loke, 2015) into the analysis will be discussed further below. Figure 3 shows the pseudosection of the MG apparent chargeability raw data collected along the first section (64 electrodes) of profile 1 before (top row) and after (second row) the removal of nondecaying curves. Measurements associated with erratic curves, i.e., with large RSMD, were not removed in this step because they are mainly related to larger separation between electrodes and, thus, to deeper information, as can be observed in Figure 3 (bottom row). As we mentioned before, one premise of our analysis is to preserve as many deep measurements as possible.

Figure 3. Pseudosections of the total chargeability measurements collected along the first section (64 electrodes) of profile 1, with MG configurations for the unfiltered data set (first plot) and following the removal of IP measurements associated to nondecaying curves (second plot) as well as the associated goodness of fit values as defined in equation 3 (third plot). Superimposed pixels in the pseudosections are related to measurements associated to the same position in the representation, but not necessarily in the subsurface.

Construction of a reference curve and second filter

To this point, each decay curve has been fitted independently, which can still result in a high spatial variability of the apparent total chargeability readings, as observed in Figure 3. In particular, the first filter does not remove those readings characterized by anomalously high total chargeability values associated with a (smoothly) decaying curve. However, due to the nature of the imaging measurements, we expect apparent total chargeability values to vary in a relatively gradual manner across the pseudosection. Measurements lacking spatial correlation with neighbor readings clearly indicate systematic errors and need to be removed before the inversion as outliers.

Thus, in the second step of the DCA, we perform an analysis of the spatial consistency of the recorded decay curves. To this end, we first construct a

reference decay curve taking into account all quadrupole measurements associated with the same injection dipole. Outliers are then identified as those measured decay curves related to a magnitude that largely varies from the magnitude of the reference curve. To minimize the effect of random noise in this step, we work with the fitted power-law model instead of the measured decay curve. The reference curve is computed as the median value of the apparent chargeability of each IP window of the MM fitted curves for measurements collected within the same current injection. For the i th IP window, the apparent chargeability ($m_{r,i}$) of the reference curve is written as

$$m_{r,i} = \text{median}(mf,1(t_i), mf,2(t_i), \dots, mf,M(t_i)). \quad (4)$$

The use of the fitted power law instead of the actual readings aims at reducing the influence of noisy curves, leading to a smooth reference curve. To avoid a distortion of the reference curve due to the effect of nondecaying curves, only measurements remaining after the first filtering step are taken into account. Figure 4 illustrates the shape and position of the reference curves for MG measurements considering three different lengths in the potential dipoles (skip 0, skip 1, and skip 2) and the corresponding spread of the current dipole.

Figure 4. Plots of the measured decay curves MDC, fitted decay curves, and the reference curve after first filter (removal of nondecaying curves) of MG measurements for (a) small, (b) medium, and (c) maximum lengths in the current dipole.

Once the reference curve is defined for each subset, it is shifted along the vertical axis minimizing the rmsd between the reference curve and the fitted curve. Outliers are then defined as those readings that require a large vertical shift within the entire data set. To define numeric and, thus, automatable criteria for the filtering, we (1) quantify the “upshift” (kuku) or “downshift” (kdkd) necessary for the reference curves to fit the corresponding measurements and (2) compute the standard deviation of the shift values (kuku and kdkd) within the data set (i.e., for all current injections). Outliers are then defined as those measurements associated with a shift value (kuku, kdkd) larger than three times the standard deviation for the entire data set. In Figure 5, we present the pseudosection for DD and MG measurements after removal of outliers based on the filtering with the reference curve. Plots in Figure 5 demonstrate that for the measurements discussed here, both configurations have a consistent performance and are related to consistent values in the measured total chargeability, permitting to validate the results from the DCA in MG configurations with those obtained by means of the NRA with DD arrays.

Figure 5. Pseudosections for data sets collected with MG and DD configurations after removal of nondecaying curves (filter 1) and spatially inconsistent measurements following the comparison with the reference curve (filter 2) from the DCA.

Standard deviation estimate and bin analysis

In the third step, we compute the DCA misfit $\Delta m_{DCA,i}$ between the measured decay curve and the power-law model fitted in step one for all measurements after applying filters one and two. For the i th IP window, the DCA misfit is defined as

$$\Delta m_{DCA,i} = m_f(t_i) - m_{m,i}. \quad (5)$$

This allows us to quantify the temporal instability (i.e., erratic behavior) of the measured signal and estimate the standard deviation of the chargeability measurement.

We propose to use the misfit $\Delta m_{DCA,i}$ between the fitted and measured decay curves in a similar way as other authors used the misfit between normal and reciprocal readings to describe the random error of the total chargeability readings of a data set (Slater and Binley, 2006; Flores Orozco et al., 2012b). To quantitatively evaluate this approach, Figure 6 shows the DCA and NRA misfits of the same DD data set, both in function of the respective transfer resistances $R=U/IR=U/I$. The general dependence of the misfit on the transfer resistance is consistent for the DCA and NRA; namely, a decrease in the misfit is associated with an increase in the value of the associated transfer resistance. The data error for chargeability measurements ($sp(m)sp(m)$) can be modeled using a power law as proposed by Flores Orozco et al. (2012b) for phase measurements:

$$s_p(m) = aR^b, \quad (6)$$

with $b < 0$, as noted in Flores Orozco et al. (2012b), to account for the decrease in the chargeability data error for increasing the associated transfer resistances. Note that instead of adjusting the error-model parameters a and b to the actual misfit $\Delta m_{DCA,i}$, we follow the methodology described in Flores Orozco et al. (2012b), based on a partitioning of the data into several bins with respect to the transfer resistance (here 10 bins), in which the error model (equation 6) is fitted to the standard deviation computed for each bin. Such procedure honors the assumption that random error can be described by its standard deviation. An alternative approach is to define a constant error model based on the

standard deviation of the misfits of the entire data set, as proposed by Slater and Binley (2006), which would assume $b=0$ in equation 6. However, such approach ignores the dependence of the IP data error on the signal strength, as discussed in Flores Orozco et al. (2012a, 2012b) and recently in Binley et al. (2016).

Figure 6. Chargeability error estimates based on DCA and NRA misfits plotted as a function of the transfer resistances

Error model for the resistance measurement

To obtain an estimate for the error of the transfer resistance measurement, we propose to fit a rational function to the standard deviation of the same binned misfits of the apparent total chargeability values used before, based on the following model:

$$sr(m)=cR+d, \quad (7)$$

where the coefficients c and d are the fitting parameters and $sr(m)$ refers to the error model of the chargeability as a function of the resistance. This is an empirical approach that honors the assumption that the resistance misfit increases with increasing transfer resistances (e.g., LaBrecque et al., 1996; Slater et al., 2000) and that the random error causing the erratic behavior observed in the measured decay curves affects the transfer resistances readings in a similar way. Thus, we use the DCA misfit as a proxy to quantify the resistance error as well. Figure 7a shows that this rational model also adjusts the variation of the $\Delta mDCA$ misfits. For comparison, Figure 7b also shows that the normal-reciprocal misfit in resistance measurements follows the same pattern, when plotted as a function of the inverse of the associated transfer resistance. Significant deviations from the power-law error model (equation 6) only appear at large transfer resistances. Now, we insert the same fitting parameters into the linear model:

$$s(R) = c + dR, \quad (8)$$

where $s(R)$ is the error model for resistance measurements, widely used (La Brecque et al., 1996; Slater et al., 2000) to describe the error of the transfer resistance measurement. Such a model implies that error parameters for low resistances are defined by the absolute error (c in

equation 8 for $R < 1 \Omega R < 1 \Omega$), whereas the error is a percentage of the measured resistance for larger values (dd in equation 8 for $R > 1 \Omega R > 1 \Omega$).

Figure 7. Distribution of (a) the DCA chargeability misfit and (b) the NRA transfer resistance misfit as a function of the transfer resistances. The black solid line shows the rational model adjusted to the binned DCA chargeability, which is then used to describe the error of the transfer resistance measurements.

Following this strategy, error parameters for apparent total chargeability and transfer resistance were defined for each TDIP profile separately, to account for variations of measurement quality across the floodplain.

Results

To investigate the suitability of our methodology to identify measurements affected by systematic errors, we compare in Figure 8 the DD total chargeability pseudosection for profile 1 after the removal of outliers following steps 1 and 2 from our DCA approach and following the NRA. For the latter, outliers were defined as measurements with a normal-reciprocal misfit larger than two times the standard deviation of all NRA misfits of the data set (see Flores Orozco et al., 2012a). Plots in Figure 8 reveal that the DCA and NRA identify similar outliers for an exemplary DD data set. We present in Table 1 a summary of the total measurements for each profile for the configurations DD and MG, as well as the percentage of the readings removed as outliers following the NRA as well as steps 1 and 2 of the proposed DCA. Table 1 demonstrates that both approaches have a similar performance regarding the number of measurements identified and removed as outliers. As mentioned in the “Introduction” section, the NRA is not suited to be applied to MG data; thus, for such measurements, we only compare the data removed (from the total) after each step of the DCA. Figure 8 reveals that the DCA filter removes fewer measurements associated with relatively high total chargeability values and/or small separations between electrodes. This illustrates the main difference between the two approaches. While the DCA only evaluates the similarity of all measured decay curves of a subset, the NRA is sensible to variations in the offset of the decay curves, the magnitude of which is higher at small dipole spacing.

Figure 8. Pseudosections for DD data collected along the first section (64 electrodes) of profile 1 after the removal of outliers as defined by (a) the proposed DCA and (b) the widely used NRA.

Regarding the quantification of random error for the transfer resistances and total chargeability measurements, in Figure 9, we present the comparison of the adjusted models following steps 3 and 4 of the proposed DCA and the NRA. Figure 9 reveals the possibility to solve for consistent error parameters. Histograms of the transfer resistances and phase-shift values, presented in Figure 9, reveal variations in the data sets due to the different filters applied in the DCA and NRA; such variations explain the slight differences in the error models obtained by the two techniques. The higher S/N in resistance measurements during the collection of normal and reciprocals lead to the estimation of lower error parameters for the inversion of the resistivity than those computed by the DCA, which is based on voltage readings after switching the current off. Nevertheless, plots of the inverted magnitude of the complex resistivity (hereafter resistivity, $\rho\rho$) reveal consistent results following both approaches, as presented in Figure 10, clearly demonstrating the applicability of the DCA technique for the quantification of resistance data error in TDIP imaging.

Figure 9. Comparison of error models (left column) and histograms of filtered raw data (right column) following the proposed DCA and the widely used NRA. Error models and histograms are presented for (a) transfer resistance and (b) the apparent phase shift data.

Figure 10. Resistivity imaging results for data processed after (a) the proposed DCA and (b) widely used NRA. Images obtained from the inversion of mixed DD and MG configurations collected along the first segment (64 electrodes) of profile 1.

Plots in Figure 10 present the electrical resistivity images obtained from the inversion of measurements collected along the first segment of profile 1 (64

electrodes) after data processing and error quantification using NRA and the DCA. Inversion results following the two different approaches yield practically the same resistivity images characterized by three units: Close to the ground surface ($>3\text{ mbgs}$), high resistivity values ($>1000\Omega\text{m}$) are associated to the unsaturated materials mainly composed of gravels and sands, a few centimeters below the clay top soil. The modest resistivity values ($100\text{--}400\Omega\text{m}$) are associated to the confined aquifer in fluvial sediments (e.g., dominating sands) and extend between 3 and 9 m depth; at the bottom, the low electrical resistivity values are related to the Mancos Shale formation. Variations in the actual depth of the aquifer are also reported from drillings on the floodplain (further information about the Shiprock site is available at U.S. Department of Energy, 2017).

Figure 11 presents a comparison of the imaging results, as obtained for the DCA and the NRA, for the polarization effect expressed in terms of the phase shift of the complex electrical resistivity (hereafter phase, ϕ). Both phase images presented in Figure 11 consistently resolve the main geologic units; the low phase values correspond to the unsaturated clay-rich top layer and the low permeable Mancos Shale at the bottom, whereas the intermediate to high phase values are associated with the sandy-gravel aquifer material. The imaging results presented in Figure 11 clearly show that the DCA analysis permits the inversion of quantitatively similar results to those obtained by the NRA. Analysis of all 22 profiles measured at the Shiprock site revealed consistent imaging results. However, a more detailed discussion of the electrical images is beyond the scope of this methodological study.

Figure 11. IP imaging results in terms of the phase of the complex electrical resistivity for data processed after (a) the proposed DCA and (b) widely used NRA. Images obtained from the inversion of mixed DD and MG configurations collected along the first segment (64 electrodes) of profile 1.

Discussion

An important and novel step in our DCA is the identification of outliers based on the analysis of the spatial correlation within the data set avoiding the arbitrary definition of threshold values and permitting an automatable processing of large TDIP imaging data without supervision. To achieve this, we define a reference curve and shift it along the yy -axis, and statistical analysis of this shifting is then used to define a confidence interval, with outliers defined as those measurements not encompassed within the limits of the confidence interval. An initial approach was to define a single reference curve and use it to evaluate the spatial consistency of the entire data set, as illustrated in Figure 12a. However, such an approach results in a

poor identification of outliers, as the definition of the interval of confidence renders too broad due to the presence of measurements with a poor S/N and large distortions in the decay curve, as observed in Figure 12. To overcome this, we opted for a partitioning of the imaging data set in smaller subsets and define the reference curve and confidence interval for each of those subsets separately. Here, it is important to warrant a sufficient number of subsets to avoid the definition of too broad filters similar to the case of a single reference curve, as well as a sufficient number of measured decay curves in each subset to avoid the definition of narrow confidence intervals and the removal of acceptable measurements. Furthermore, considering that the DCA approach penalizes the magnitude of the total chargeability, it is necessary to have some dynamic in the measured values contained in each subset (i.e., variations in the measured decay curves) so that the adjustments of the reference take place over a broad range and minimize the risk of removing a large number of acceptable measurements as outliers.

Figure 12. Presentation of the intervals of confidence after shifting of the reference curve based on two approaches: (1) grouping all measurements in a single set (a) and (2) subsets defined by the measurements collected at the same level of the pseudosection (c-e). The pseudosection (b) presents the injected current associated to each quadrupole measurement and highlights the three depth levels displayed in the bottom row.

Grouping the measurements based on the current injection provides a good trade-off regarding the number and size of the subsets. Furthermore, such approach takes into account that imaging data sets are collected with tens of electrodes with variable contact resistances, resulting in changes of the injected current along the imaging plane (as illustrated in Figure 12b), which also impose changes in the S/N of the recorded voltages. Thus, our approach compares measurements collected due to the same imposed electrical field and a relative volume of influence; thus, outliers can be defined as those readings revealing an abrupt change in the measured decay curve, based on the comparison with the reference model. Moreover, analysis of measurements based only on those collected for a given current injection permits to perform the DCA during data collection, in case that real-time information is required, for instance, in monitoring applications.

A second approach considers the definition of subsets associated to the depth in the pseudosection, which aims at the comparison of readings collected with the same separation between electrodes, another factor controlling the S/N. To illustrate this, Figure 12 presents the measured curves for shallow (Figure 12c), intermediate (Figure 12d), and deeper

(Figure 12e) positions in the pseudosection, as well as the corresponding reference curve and computed interval of confidence. Such plots reveal that the shallow measurements (Figure 12c) contain a larger number of measurements than those related to deeper positions (Figure 12d); yet, it permits the comparison of curves with a roughly similar quality in the decay curves, which is a significant advantage of such an approach. Furthermore, such approach can be used in imaging data sets collected with single-channel instruments or Wenner configurations, in which every potential measurement is made with a different current dipole. Although not presented here, we observed similar results regarding the number of measurements removed as outliers, and the distribution of data misfit and error parameters as the last two steps of the DCA are independent on the definition of subsets for the analysis of the reference curve. However, grouping the data set based on the depth level of the pseudosection needs to be performed carefully, as these subsets may contain decay curves associated to different S/N related to variations in the injected current (Figure 12b) and also due to lateral changes in the electrical properties of the subsurface (see Figures 5 and 8).

Analysis of the 22 TDIP profiles reveals that the rule described above applies to most of the cases; however, the filter might need to be adjusted for noisy or very consistent (clean) data sets. In the former case, the computed reference curve is obtained by averaging poorly comparable curves, leading to a nonrepresentative reference curve and only a poor filtering, whereas for the clean data sets, we do need to adjust the filter to avoid the filtering of valid measurements. In Table 2, we present a first approach to permit an automatable identification of the “noisy” and “clean” data sets, as well as a rule to define the maximum up- and down-shifts k_{uku} and k_{dkd} and to adjust the maximum deviations accepted.

The case of noisy data sets poses further challenges considering that the computed k_{uku} and k_{dkd} values could vary over a broad range resulting in an insufficient detection of outliers during the second filtering step. To overcome this possible problem, we propose a further filtering step based on the analysis of the histogram of the measured total chargeabilities of the entire data set. Such analysis considers that, for an adequate number of bins, the measured total chargeability without spatial correlation should appear as isolated clusters separated from the main distribution of valid measurements. Hence, the occurrence of empty bins can be used to identify spatial inconsistencies and to define the maximum and minimum values for total chargeability readings. Measurements outside the range defined in this manner can then be removed as outliers. The efficiency of such an approach depends largely on the number of bins selected for the analysis. Based on the normal-reference rule provided by Sturges (1926) and modified by Larson (1975), we define the number of bins (nb) as

$$nb = 1 + 4.5 \log_{10} n, \quad (9)$$

where nn refers to the total number of measurements remaining in the data set after the second filter of the DCA. Although not discussed here, such histogram analysis could also be performed for the NRA or as a preliminary filter to remove readings associated to electrodes with high contact resistance or related to low current injections.

Our DCA is based on fitting the measured decays by means of a simple power-law model, which represents the voltage decay after switching the current injection off. As mentioned above, power-law models can be considered the time-domain equivalent of the frequency-domain constant phase model (van Voorhis et al., 1973). Further tests also included the fitting of the measured decay curve with a Cole-Cole model (CCM) which is the dispersion model commonly used to describe the frequency dependence of the IP response (Pelton et al., 1978) and lately has also been used to model the decay curve in TDIP measurements (e.g., Fiandaca et al., 2012). Although the implementation of the CCM into our analysis also reveals consistency in the computed total chargeability values and the definition of outliers, the goodness of fit and the retrieved Cole-Cole parameters strongly depend on the initial values defined for the fitting — in particular for noisy data. The processing of imaging data sets requires the fitting of hundreds to thousands of measurements; thus, a robust model with a small number of parameters is better suited. Furthermore, it has been demonstrated that not all IP signatures can be described by a CCM (e.g., Nordsiek and Weller 2008; Flores Orozco et al., 2012b, 2013). Hence, we consider that fitting of the power-law model presented in equation 2 for the detection of outliers and quantification of data error is more than sufficient, and its advantages considering robustness and the weak dependency on the initial values outweigh by far the possible lack of a theoretical justification.

It is also worth highlighting that the use of the power-law model is strictly limited to the estimation of the error parameters and has no further implication on the inversion itself. Actually, as mentioned above, the conversion of the TDIP chargeability to frequency-domain phases assumes a constant-phase model (e.g., van Voorhis et al., 1973; Kemna et al., 1999), which is also not a Cole-Cole type response. Furthermore, the inversion of the data is performed on the computed total chargeability; i.e., only the magnitude of the polarization is taken into account and no information about the shape of the measured decay curve. However, recent inversion schemes are based on the modeling of the full waveform of the received voltage (e.g., Fiandaca et al., 2012a, 2012b), in which the shape of the decay plays an important role. Moreover, the DCA approach can be used only for the removal of outliers (steps 1 and 2), and inversion can be performed using robust schemes (Morelli and LaBrecque, 1996; Kemna, 2000), which do not require information on the data error.

A particular case to take into account is the occurrence of negative chargeability related to high polarization effects in areas of negative sensitivity, as presented in detail in the study by Dahlin and Loke (2015). These authors observe that for certain electrode configurations and under certain subsurface conditions, voltage readings after current switch off can be negative and increase with time (voltage values tending to zero). Yet it is important to differentiate actual negative IP effects from the occurrence of systematic error resulting in nondecaying curves (see Figure 2d) related to capacitive and inductive coupling, as also discussed by Dahlin and Loke (2015). Furthermore, keeping measurements related to negative decaying curves should be considered only if the inversion algorithm can model such negative IP effects.

Recent investigations have also demonstrated the possibility to significantly reduce acquisition times, for instance, by deploying 100% duty cycles (Olson et al., 2015) and modeling the entire waveform. Yet we note here that such measurements might also be affected by capacitive and inductive coupling, and the distortions in the signatures due to random error. Therefore, the analysis that we present can be applied to full waveform data as a first filtering of the data (i.e., to identify and remove outliers). In this regard, further investigations could focus on the incorporation of the full waveform analysis (i.e., penalize not only the magnitude but also the shape of the decay curve), as well as the incorporation of the error parameters obtained from our DCA into the inversion of the frequency dependence of TDIP using the formulation of the waveform, as well as into the analysis of monitoring data sets.

Conclusion

We have presented a new methodology for the processing of TDIP imaging data sets entirely based on the analysis of the IP decay curve. Analysis of the data was performed on TDIP measurements using DD and MG configurations performed in an extensive area (approximately 12 ha) in a near-surface investigation (depth of investigation limited to 7 m). Our results demonstrate that our approach reliably identifies outliers and provides an adequate quantification of the data error. Our methodology is able to quantify magnitude and distribution of the data error in a very consistent manner comparable with the widely used NRA. In contrast to the latter, the new method does not require the collection of reciprocal readings, which reduces the acquisition time by 50% and makes field surveys much more efficient. Furthermore, based on our method, a quantitative data error description is also possible for data collected with configurations other than DD, e.g., pole-dipole or MG. Inverted chargeability images obtained from DCA-processed data also reveal consistency with those obtained using NRA.

Acknowledgments

This material is partially based upon work supported through the Lawrence Berkeley National Laboratory's Watershed Function Scientific Focus Area.

The U.S. Department of Energy (DOE), Office of Science, and Office of Biological and Environmental Research (BER) funded the work under contract DE-AC02-05CH11231 (Lawrence Berkeley National Laboratory; operated by the University of California). The research supported by the SLAC Science Focus Area (SFA) program is also supported by DOE-BER under SLAC FWP 10094 and by the POTHAL project funded by the Austrian Federal Ministry of Education in frame of the Raw-Materials initiative. We thank L. Slater and two anonymous reviewers for their constructive comments that helped to improve the manuscript.

References

- Atekwana, E. A., and L. D. Slater, 2009, Biogeophysics: A new frontier in Earth science research: *Reviews of Geophysics*, 47, RG4004, doi: <https://doi.org/10.1029/2009RG000285>.
- Binley, A., J. Keery, L. Slater, W. Barrash, and M. Cardiff, 2016, The hydrogeologic information in cross-borehole complex conductivity data from an unconsolidated conglomeratic sedimentary aquifer: *Geophysics*, 81, no. 6, E409-E421, doi: <https://doi.org/10.1190/geo2015-0608.1>.
- Binley, A., and A. Kemna, 2005, DC resistivity and induced polarization methods, in Y. Rubin and S. Hubbard, eds., *Hydrogeophysics*: Springer, 129-156.
- Binley, A., A. Ramirez, and W. Daily, 1995, Regularised image reconstruction of noisy electrical resistance tomography data: 4th Workshop of the European Concerted Action on Process Tomography, European Concerted Action on Process Tomography.
- Dafflon, B., Y. Wu, S. S. Hubbard, J. T. Birkholzer, T. M. Daley, J. D. Pugh, J. E. Peterson, and R. C. Trautz, 2012, Monitoring CO₂ intrusion and associated geochemical transformations in a shallow groundwater system using complex electrical methods: *Environmental Science and Technology*, 47, 314-321, doi:<https://doi.org/10.1021/es301260e>.
- Dahlin, T., and V. Leroux, 2012, Improvement in time-domain induced polarization data quality with multi-electrode systems by separating current and potential cables: *Near Surface Geophysics*, 10, 545-565.
- Dahlin, T., V. Leroux, and J. Nissen, 2002, Measuring techniques in induced polarisation imaging: *Journal of Applied Geophysics*, 50, 279-298, doi: [https://doi.org/10.1016/S0926-9851\(02\)00148-9](https://doi.org/10.1016/S0926-9851(02)00148-9).
- Dahlin, T., and M. H. Loke, 2015, Negative apparent chargeability in time-domain induced polarisation data: *Journal of Applied Geophysics*, 123, 322-332.
- Dahlin, T., and B. Zhou, 2006, Multiple-gradient array measurements for multichannel 2D resistivity imaging: *Near Surface Geophysics*, 4, 113-123.

Doetsch, J., G. Fiandaca, E. Auken, A. V. Christiansen, A. G. Cahill, and R. Jakobsen, 2015a, Field-scale time-domain spectral induced polarization monitoring of geochemical changes induced by injected CO₂ in a shallow aquifer: *Geophysics*, 80, no. 2, WA113-WA126, doi: <https://doi.org/10.1190/geo2014-0315.1>.

Doetsch, J., T. Ingeman-Nielsen, A. V. Christiansen, G. Fiandaca, E. Auken, and B. Elberling, 2015b, Direct current (DC) resistivity and induced polarization (IP) monitoring of active layer dynamics at high temporal resolution: *Cold Regions Science and Technology*, 119, 16–28, doi:<https://doi.org/10.1016/j.coldregions.2015.07.002>.

Fiandaca, G., E. Auken, A. V. Christiansen, and A. Gazoty, 2012a, Time-domain-induced polarization: Full-decay forward modeling and 1D laterally constrained inversion of Cole-Cole parameters: *Geophysics*, 77, no. 3, E213–E225, doi: <https://doi.org/10.1190/geo2011-0217.1>.

Fiandaca, G., J. Ramm, A. Binley, A. Gazoty, A. V. Christiansen, and E. Auken, 2012b, Resolving spectral information from time domain induced polarization data through 2-D inversion: *Geophysical Journal International*, 192, 631–646, doi: <https://doi.org/10.1093/gji/ggs060>.

Flores Orozco, A., A. Kemna, C. Oberdörster, L. Zschornack, C. Leven, P. Dietrich, and H. Weiss, 2012a, Delineation of subsurface hydrocarbon contamination at a former hydrogenation plant using spectral induced polarization imaging: *Journal of Contaminated Hydrology*, 136–137, 131–144, doi:<https://doi.org/10.1016/j.jconhyd.2012.06.001>.

Flores Orozco, A., A. Kemna, and E. Zimmermann, 2012b, Data error quantification in spectral induced polarization imaging: *Geophysics*, 77, no. 3, E227–E237, doi: <https://doi.org/10.1190/geo2010-0194.1>.

Flores Orozco, A., M. Velimirovic, T. Tosco, A. Kemna, H. Sapion, N. Klaas, R. Sethi, and B. Leen, 2015, Monitoring the injection of microscale zero-valent iron particles for groundwater remediation by means of complex electrical conductivity imaging: *Environmental Science and Technology*, 49, 5593–5600, doi:<https://doi.org/10.1021/acs.est.5b00208>.

Flores Orozco, A., K. H. Williams, and A. Kemna, 2013, Time-lapse spectral induced polarization imaging of stimulated uranium bioremediation: *Near Surface Geophysics*, 11, 531–544.

Flores Orozco, A., K. H. Williams, P. E. Long, S. S. Hubbard, and A. Kemna, 2011, Using complex resistivity imaging to infer biogeochemical processes associated with bioremediation of an uranium-contaminated aquifer: *Journal of Geophysical Research: Biogeosciences*, 116, 2156–2206, doi:<https://doi.org/10.1029/2010JG001591>.

Gazoty, A., G. Fiandaca, J. Pedersen, E. Auken, A. V. Christiansen, and J. K. Pedersen, 2012, Application of time domain induced polarization to the

mapping of lithotypes in a landfill site: *Hydrology and Earth System Sciences*, 16, 1793–1804, doi: <https://doi.org/10.5194/hess-16-1793-2012>.

Gazoty, A., G. Fiandaca, J. Pedersen, E. Auken, and A. V. Christiansen, 2013, Data repeatability and acquisition techniques for time-domain spectral induced polarization: *Near Surface Geophysics*, 11, 391–406, doi: <https://doi.org/10.3997/1873-0604.2013013>.

Kemna, A., 2000, *Tomographic inversion of complex resistivity: Theory and application*: Der Andere Verlag.

Kemna, A., A. Binley, G. Cassiani, E. Niederleithinger, A. Revil, L. Slater, K. H. Williams, A. Flores Orozco, F.-H. Haegel, A. Hördt, S. Kruschwitz, V. Leroux, K. Titov, and E. Zimmermann, 2012, An overview of the spectral induced polarization method for near-surface applications: *Near Surface Geophysics*, 10, 453–468.

Kemna, A., E. Räckers, and L. Dresen, 1999, Field applications of complex resistivity tomography: *69th Annual International Meeting, SEG, Expanded Abstracts*, 331–334.

LaBrecque, D. J., M. Miletto, W. Daily, A. Ramirez, and E. Owen, 1996, The effects of noise on Occam's inversion of resistivity tomography data: *Geophysics*, 61, 538–548, doi: <https://doi.org/10.1190/1.1443980>.

Larson, H. J., 1975, *Statistics: An introduction*: Wiley, 15.

Morelli, G., and D. J. LaBrecque, 1996, Robust scheme for ERT inverse modelling: *Symposium on the Application of Geophysics to Engineering and Environmental Problems*: SEG, 629–638.

Nordsiek, S., and A. Weller, 2008, A new approach to fitting induced-polarization spectra: *Geophysics*, 73, no. 6, F235–F245, doi: <https://doi.org/10.1190/1.2987412>.

Olsson, P. I., T. Dahlin, G. Fiandaca, and E. Auken, 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, doi: <https://doi.org/10.1016/j.jappgeo.2015.08.009>.

Olsson, P. I., G. Fiandaca, J. J. Larsen, T. Dahlin, and E. Auken, 2016, Doubling the spectrum of time-domain induced polarization by harmonic de-noising, drift correction, spike removal, tapered gating and data uncertainty estimation: *Geophysical Journal International*, 207, 774–784, doi: <https://doi.org/10.1093/gji/ggw260>.

Pelton, W. H., S. H. Ward, P. G. Hallof, W. R. Sill, and P. H. Nelson, 1978, Mineral discrimination and removal of inductive coupling with multifrequency IP: *Geophysics*, 43, 588–609, doi: <https://doi.org/10.1190/1.1440839>.

Slater, L., and A. Binley, 2006, Synthetic and field-based electrical imaging of zerovalent iron barrier: Implications for monitoring long-term barrier

performance: *Geophysics*, 71, no. 5, B129–B137,
doi: <https://doi.org/10.1190/1.2235931>.

Slater, L., A. Binley, W. Daily, and R. Johnson, 2000, Cross-hole electrical imaging of a controlled saline tracer injection: *Journal of Applied Geophysics*, 44, 85–102, doi: [https://doi.org/10.1016/S0926-9851\(00\)00002-1](https://doi.org/10.1016/S0926-9851(00)00002-1).

Sturgers, H. A., 1926, The choice of a class interval: *Journal of the American Statistical Association*, 21, 65–66,
doi: <https://doi.org/10.1080/01621459.1926.10502161>.

U.S. Department of Energy (DOE) Office of Legacy Management Data Disclaimer, 2017, <http://www.gems.lm.doe.gov/#site=SHP>, accessed December 2017.

Van Voorhis, G. D., P. H. Nelson, and T. L. Drake, 1973, Complex resistivity spectra of porphyry copper mineralization: *Geophysics*, 38, 49–60,
doi: <https://doi.org/10.1190/1.1440333>.

Wainwright, H. M., A. Flores Orozco, M. Bucker, B. Dafflon, J. Chen, S. S. Hubbard, and K. H. Williams, 2015, Hierarchical Bayesian method for mapping biogeochemical hot spots using induced polarization imaging: *Water Resources Research*, 52, 533–551,
doi: <https://doi.org/10.1002/2015WR017763>.

Weigand, M., A. Flores Orozco, and A. Kemna, 2017, Reconstruction quality of SIP parameters in multi-frequency complex resistivity imaging: *Near Surface Geophysics*, 15, 187–199.

Weller, A., L. Slater, and S. Nordsiek, 2013, On the relationship between induced polarization and surface conductivity: Implications for petrophysical interpretation of electrical measurements: *Geophysics*, 78, no. 5, D315–D325, doi: <https://doi.org/10.1190/geo2013-0076.1>.