

1 **Standard, random, and optimum array conversions from two-pole resistance data**

2 ¹Dale F. Rucker and ²Danney R. Glaser

3
4 ¹hydroGEOPHYSICS, Inc., 2302 N Forbes Blvd, Tucson, AZ 85745
5 Email: druck8240@gmail.com
6

7 ²Washington River Protection Solutions, LLC,
8 2440 Stevens Center Place, Richland, WA 99354 USA
9 Email: Dan_Glaser@rl.gov
10
11

12 **ABSTRACT**

13 We present an array evaluation of standard and nonstandard arrays over a
14 hydrogeological target. We develop the arrays by linearly combining data from the pole-pole (or
15 2-pole) array. The first test shows that reconstructed resistances for the standard Schlumberger
16 and dipole-dipole arrays are equivalent or superior to the measured arrays in terms of noise,
17 especially at large geometric factors. The inverse models for the standard arrays also confirm
18 what others have presented in terms of target resolvability, namely the dipole-dipole array has the
19 highest resolution. In the second test, we reconstruct random electrode combinations from the 2-
20 pole data segregated into inner, outer, and overlapping dipoles. The resistance data and inverse
21 models from these randomized arrays show those with inner dipoles to be superior in terms of
22 noise and resolution and that overlapping dipoles can cause model instability and low resolution.
23 Finally, we use the 2-pole data to create an optimized array that maximizes the model resolution
24 matrix for a given electrode geometry. The optimized array produces the highest resolution and
25 target detail. Thus, the tests demonstrate that high quality data and high model resolution can be
26 achieved by acquiring field data from the pole-pole array.

27 **Introduction**

28 There are many examples in the geophysical literature of electrical resistivity array
29 evaluation to determine the best means to image the subsurface. One of the most comprehensive
30 was that performed by Dahlin and Zhou (2004), where 10 standard arrays were compared in a
31 series of tests using synthetic geological models. Each array had different strengths in terms of
32 resolution, acquisition efficiency, depth of signal penetration, and signal-to-noise (S/N). Other
33 examples of array evaluation for both field and synthetically derived models included Dey et al.
34 (1975), Saydam and Duckworth (1978), Batayneh (2001), Candansayar and Basokur (2001), and
35 Seaton and Burbey (2002). Most of the studies concluded that the dipole-dipole array has very
36 high resolution and low S/N, whereas the Wenner and Schlumberger arrays have a slightly lower
37 resolution but better signal penetration and noise characteristics. The pole-pole array also has
38 high S/N, but is one of the lowest resolving arrays.

39 One means of increasing the utility of the resistivity method is to combine two or more
40 arrays together, which may take advantage of particular features of individual arrays, such as high
41 resolution and high S/N. For example, Kaufmann and Quinif (2001) and Zhou et al. (2002)

42 combined Wenner, Schlumberger, and dipole-dipole arrays to map sinkholes. Again, Dahlin and
43 Zhou (2004) noted that the imaging quality of some mixed arrays is similar to the better resolved
44 individual image and that the data from the lower resolution array provides little to no
45 improvement. Alternatively, Leontarakis and Apostolopoulos (2012) used image stacking by
46 calculating the geometric mean of resistivity from a number of arrays to produce a final model
47 that appeared to be less prone to artifacts compared to individual and mixed arrays. In all of these
48 multiple dataset and multiple model approaches, a significant amount of field and processing time
49 would be necessary to capture each of the different arrays.

50 Two separate tracks of investigation into the resistivity method have almost rendered
51 issues of resolution, acquisition efficiency, and S/N obsolete. Firstly, Sri Niwas and Israil (1989),
52 Xu and Noel (1993), and Lehmann (1995) described a means of selecting a base set of four-pole
53 electrodes from which other four-pole electrode pairs can be calculated using superposition. Thus,
54 by making a relatively small number of strategic measurements, other desired arrays can simply
55 be calculated and there would be little need to acquire multiple arrays for testing. Blome et al.
56 (2011) showed the same type of conversion for a base three-pole (i.e., pole-dipole) dataset to
57 calculate other three-pole combinations. In each case, the noise from the base 3- or 4-pole
58 combination is additive and Blome's approach would appear to be highly advantageous given that
59 only two combinations are necessary to calculate any other combination. Up to six 4-pole
60 combinations are required to cover the complete 4-pole dataset. Rucker (2012) demonstrated a 2-
61 pole to 4-pole conversion for long electrode data, where four calculations are always needed for
62 any 4-pole combination.

63 The second track of investigation includes calculating the optimal array based on
64 maximizing the subsurface resolution as defined by the inverse model resolution matrix. Stummer
65 et al. (2004) introduced the concept of deriving an optimal array configuration that is
66 computationally efficient and combines standard and nonstandard electrode combinations. Since
67 then, a number of researchers have expanded the methodology by which to search for and
68 practically use the optimal configuration, including Wilkinson et al. (2006), Loke et al. (2010), Al
69 Hagrey (2012), Wilkinson et al. (2012), and Loke et al. (2014). The resolution from the optimal
70 arrays is far superior to any standard array (e.g., pole-pole, dipole-dipole, pole-dipole,
71 Schlumberger, or Wenner). In this work we combine the two tracks of investigation to calculate
72 the optimal 4-pole array from a measured 2-pole dataset. We first compare the acquired pole-pole
73 data, converted to the standard dipole-dipole and Schlumberger arrays, to the measured standard
74 arrays over the same target. The comparison is to demonstrate the difference in measured and
75 calculated potentials and resulting target definition and resolution from inverse models of each
76 array. We then demonstrate the results from other 4-pole conversions including a randomized (as
77 demonstrated in Rucker, 2012) and optimal set. The results will demonstrate that superior arrays
78 for acquisition and modeling can be obtained with little effort.

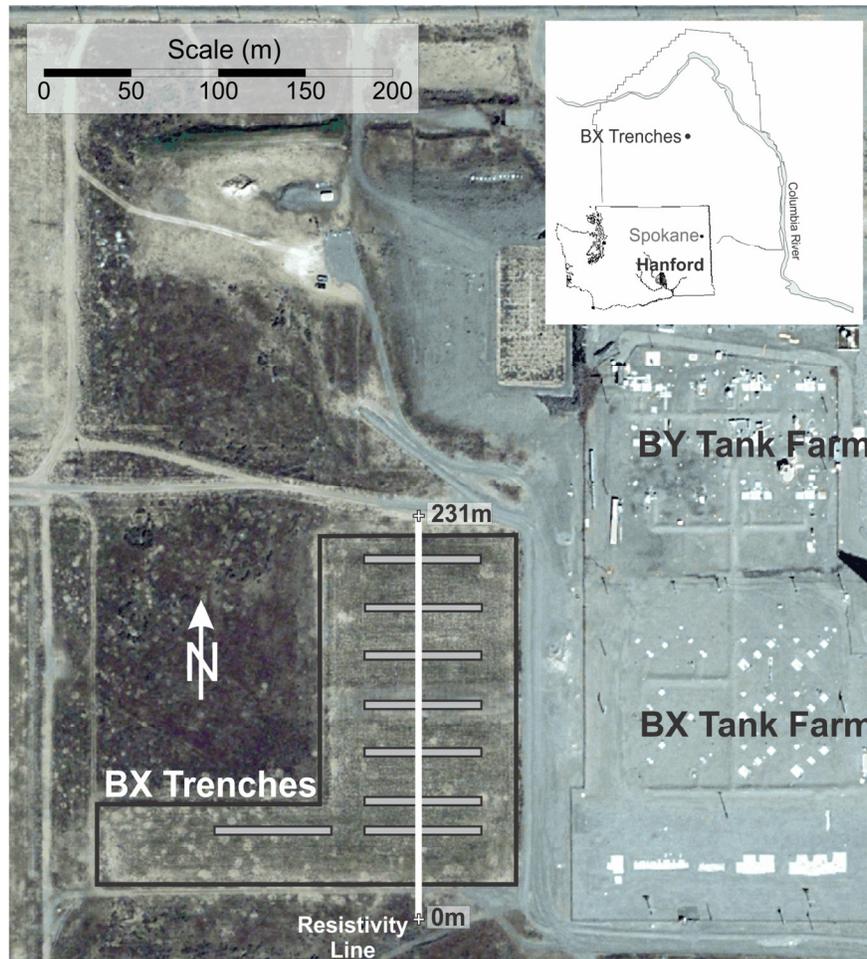
79 **Site Description**

80 Electrical resistivity data for multiple arrays were acquired over a series of infiltration
81 galleries. The galleries, or trenches as they are known, were designed to dispose liquid
82 radiological waste associated with plutonium production at the Hanford site in the mid-1950s.

83 The series of eight trenches, located to the west of the BX tank farm (Fig. 1), received 15×10^6 L
84 of sodium nitrate waste between 1954 and 1955 (Lindenmeier et al. 2002). Several steel cased
85 wells were installed for geophysical well logging to detect neutron and spectral gamma emitting
86 contaminants. In general, the spectral gamma logging revealed high Cs-137 concentrations in the
87 top 10 m of soil, and in some cases Co-60 to depths of 14 m (Rucker et al., 2013). A soil
88 characterization borehole also revealed significant nitrate concentrations from depths 17 to 61 m
89 below ground surface. The sodium nitrate was the target for electrical resistivity investigation.

90 Sediments throughout the Hanford Site are glacial-fluvial as a result of great floods that
91 swept through the Columbia Basin during the past 15,000 years. The major formations from
92 bottom to top include a Pliocene-age Ringold formation consisting of overbank deposits from the
93 ancestral Columbia River, a Pliocene-age calcified paleosol Cold Creek unit, and a Pleistocene-
94 age Hanford formation resulting from the catastrophic flood deposits of glacial Lake Missoula
95 (Gee et al., 2007). The Hanford formation can be further divided into subunits based on loose
96 boundaries of coarse and fine grained fractions. Electrically, these sediments are relatively
97 resistive compared to the sodium nitrate waste target.

98 **Figure 1. Location of the Hanford Site and resistivity study in central Washington.**



99

100

101

Array Optimization

102

103

104

105

106

107

108

109

110

111

112

113

114

115

116

117

118

119

120

The definition of optimal electrode configurations can be considered from a combination of important factors such as signal strength, depth of penetration, the ability to complete acquisition in a short period of time, and the resolving capability of the configuration. Much of the work into developing optimized arrays has been focused on the last item, where electrode pairs are chosen such that the model resolution of the subsurface is maximized. For example, Maurer et al. (2000) demonstrated with a Schlumberger sounding example that a subset of measurements contribute significantly to resolving the geological features of the subsurface while other measurements contribute very little. Diagonal elements of model resolution matrix, \mathbf{R} , indicated the relative importance of individual data points. The model resolution matrix is defined by $\mathbf{m}^{\text{fit}} = \mathbf{R}\mathbf{m}^{\text{true}}$ (Menke 1984), where \mathbf{m}^{fit} is the estimate of the model resistivities determined by the inversion process, and \mathbf{m}^{true} comprises the unknown true resistivities (Wilkinson et al., 2006). If each model cell is perfectly resolved then \mathbf{R} is the identity matrix. Later, Stummer et al. (2004) generalized the work of Maurer et al. (2000) by searching for the best subset of configurations that maximizes the model resolution by starting with a base dipole-dipole array and adding only those configurations that increase the model resolution. The added configurations were chosen from a comprehensive list and new configurations were tested incrementally using a goodness function (GF) to determine the effect on the resolution. Their work showed that non-standard electrode configurations could be chosen that greatly enhances the ability of the resistivity method to resolve important areas of the subsurface.

121

122

123

124

125

126

127

Over the last decade, effort in determining the optimal array has focused on the computational difficulty of searching for the subset of electrode configurations that provide the greatest resolution. Wilkinson et al. (2006) compared three strategies for finding the optimal set and determined that the Compare R method is more accurate but computationally slower than the original or Modified GF search. Based on its performance, Loke et al. (2010a; b) developed new algorithms for the Compare R method and used new computational hardware (the Graphical Processing Unit, or GPU) to speed the search for electrode subsets.

128

129

130

131

132

133

134

135

136

137

138

139

140

In our work, we use the Compare R method for searching the best subset of electrode pairs to increase resolution of the subsurface. Operationally, the Compare R methodology starts with a base set of electrode combinations. The high resolution of the dipole-dipole array makes it a good starting point, and the Compare R algorithm uses configurations of a unit electrode spacing for dipole length (i.e., a-spacing) and dipole separations (n-spacing) from 1 to 6. With 78 electrodes used in our study, the base dipole-dipole set for the optimal array included 435 combinations. To this base set, new combinations were added incrementally. To reduce the number of possible combinations in which to explore, those exhibiting extremely large geometric factors and other less stable configurations such as overlapping dipoles were excluded. The examples presented below, using overlapping dipoles generated from randomized combinations, confirmed the instability observed in other's work (e.g., Stummer et al., 2004; Wilkinson et al. 2006). Additionally, electrode combinations that were not symmetrical about the survey line were made symmetrical by adding the complement to the other side of the line.

141 The resolution updating procedure was conducted iteratively by adding a small number of
142 combinations with each trial. In this case, we added 5% to the number of electrode combinations
143 with each iteration. The model resolution matrix was then updated and compared to the previous
144 iteration. Those combinations that increased the resolution were kept; those combinations that
145 worsened the resolution were discarded. The procedure was terminated when the number of
146 optimal combinations reached 8,000.

147 **Methodology**

148 The following section describes arrays acquired and calculated from transfer resistance
149 data for conventional arrays, random arrays, and the optimized array based on the Compare R
150 method (Loke et al., 2010).

151 Conventional Arrays

152 The survey line for the array conversion demonstration was placed perpendicular to the
153 series of BX trenches (Fig. 1). The line was 231 m with 78 electrodes spaced every 3 m. The
154 resistivity data were acquired with the SuperSting R8 (by AGI, Austin, TX). The complete
155 dataset with all measured arrays included the Schlumberger array with 1,482 measurements,
156 dipole-dipole array with 580 measurements, and pole-pole array with 3,003 measurements. The
157 remote poles were placed 800m and 1200m away for the transmitting and receiving dipoles,
158 respectively. No reciprocal measurements were taken. However, the SuperSting R8 output file
159 contains a repeat voltage measurement error based on two measurements taken consecutively.
160 The final voltage is recorded as the average of both measurements and the error is calculated as
161 the difference between the measurements divided by the averaged resistance which is then
162 recorded as a percentage.

163 A comparison of the raw resistance data are shown in Fig. 2. The data are plotted as a
164 pseudoplot with distances along the line taken as an average between the transmitter and receiver
165 electrode positions for pole-pole and dipole-dipole, and as the average of the internal receiver
166 electrodes for the Schlumberger array. The data are shown to segregate naturally by their a-
167 spacing value, which is the (di)pole distance for pole-pole and dipole-dipole arrays or the distance
168 between transmitter electrodes for the Schlumberger array. The signal strength for the pole-pole
169 array is shown to be significantly higher than the dipole-dipole and Schlumberger arrays. A
170 minimum resistance value of 0.25 ohms was obtained for the pole-pole array relative to 0.0053
171 ohms for dipole-dipole and 0.0012 ohms for the Schlumberger array. Unexpectedly, the minimum
172 resistance values for the Schlumberger array are lower than those of the dipole-dipole array.
173 However, the average resistance for the Schlumberger array is 30% higher than the resistance for
174 the dipole-dipole array.

175 The reconstructed 4-pole resistance from measured 2-pole resistance data is calculated by
176 (Rucker, 2012):

$$177 \quad U_{ABMN} = U_{AM} - U_{AN} - U_{BM} + U_{BN} \quad (1)$$

178 where subscripts A and B refer to the transmission electrode pair and M, N refer to the receiving
179 electrode pair needed for the completion of the resistance (U) measurement. For the error (or
180 noise) of each data pair, the following relationship is used:

181

$$182 \quad E_{ABMN} = E_{AM} + E_{AN} + E_{BM} + E_{BN} \quad (2)$$

183

184 Equation (1) was used to calculate the equivalent Schlumberger and dipole-dipole arrays
185 from measured pole-pole data and the results of the calculation can be observed in Fig. 2 in direct
186 comparison to the measured data. The pseudoplots of each calculated array are shown to align
187 well with the measured data and the scatterplot of measured vs. calculated show very little
188 deviation from a near perfect fit. The measured data from Schlumberger and dipole-dipole arrays
189 are shown to have some noise, but the calculated values for those particular pairs appear to be less
190 noisy due to the higher quality pole-pole data.

191 The resistance data from the three arrays were inverted individually to build a
192 representation of subsurface resistivity. There are many published articles on electrical resistivity
193 inversion to which the reader may refer (e.g., Loke et al., 2013 and the references therein). To
194 keep the analysis simple, only the measured data were modeled. Given the goodness of fit for the
195 calculated versus measured data, the inverse models for the calculated data would not have shown
196 much difference relative to the models of the measured data. RES2DINVx64 was used for the
197 inversion and the three datasets converged to a root mean square (RMS) error less than 5% within
198 four iterations. The pole-pole array converged with an RMS of less than 1.5% in four iterations,
199 thus providing a qualitative noise comparison among the three arrays.

200 Figs. 3 and 4 show the results of the inverse modeling. In Fig. 3, contours of the
201 logarithmically-transformed resistivity show similar features among the three arrays. There is a
202 large low resistivity target between a distance of 80 and 100 m, which is likely the direct result of
203 nitrate-laden waste disposed in the series of BX trenches. Other near surface resistive features can
204 also be traced within all three models, for example at a distance of 80 and 180m. Major
205 differences between the arrays can be seen in the depth of investigation, where the pole-pole
206 images significantly deeper than the other two arrays, and in the shape and amplitude of the low
207 resistivity target. For ease of plotting, the pole-pole array has been truncated to a depth of 50m,
208 but the entire model extended to a depth of 162m.

209

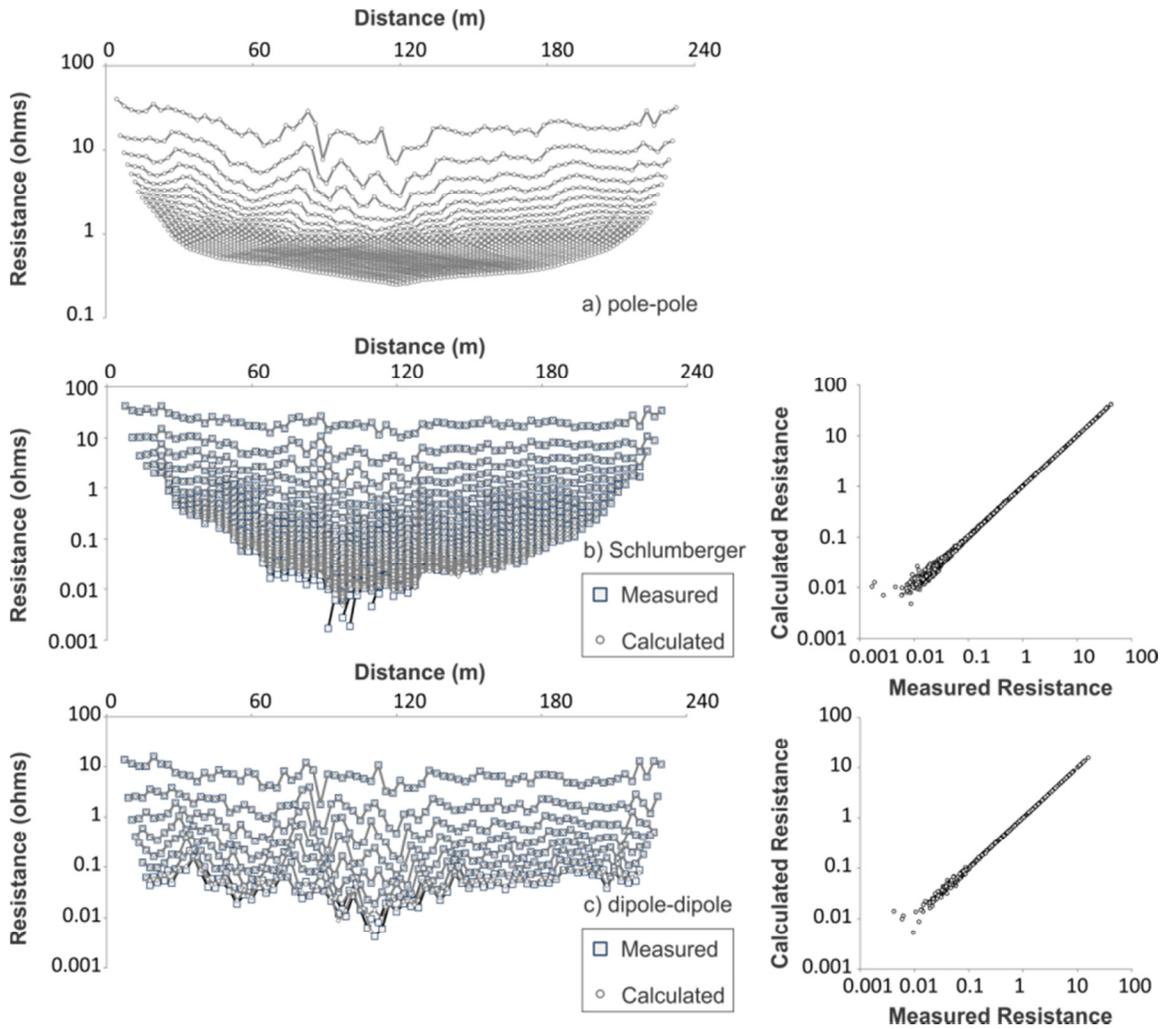
210

211

212

213

214 **Figure 2. Pseudoplot of data acquired with a) pole-pole array, b) Schlumberger array, and**
215 **c) dipole-dipole array. For the Schlumberger and dipole-dipole array, both measured and**
216 **calculated resistances are compared as a pseudoplot and scatterplot.**



217

218

219

220

221

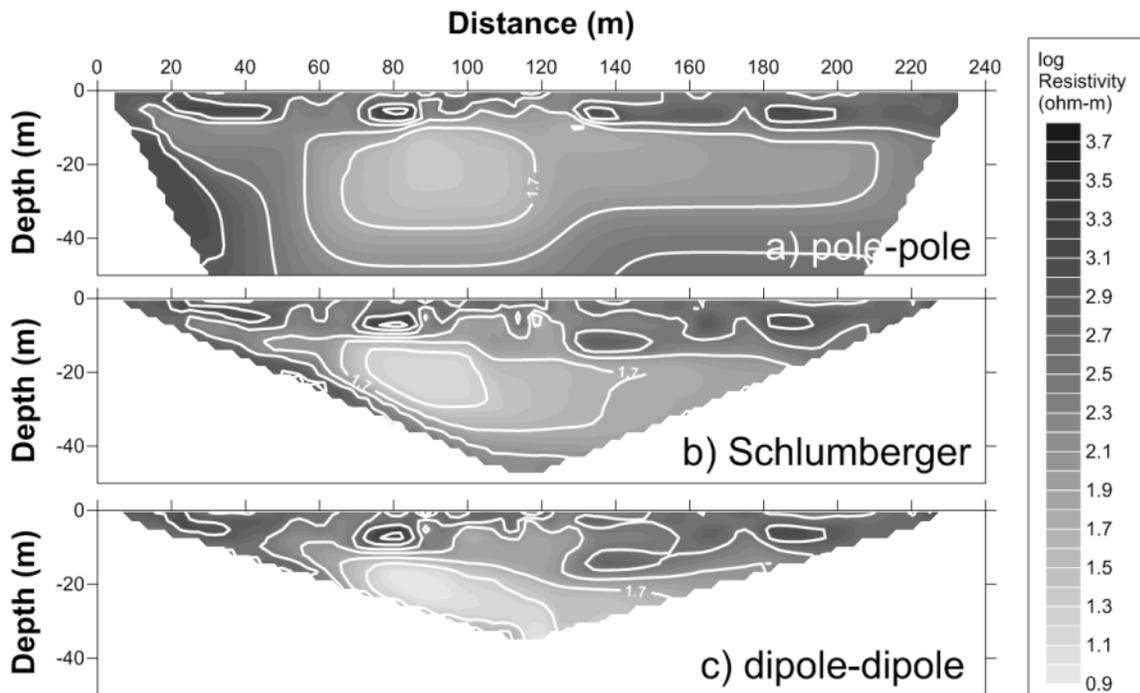
222

223

224

225

226 **Figure 3. Inverse model results using measured data for a) pole-pole, b) Schlumberger, and**
227 **c) dipole-dipole arrays.**



228

229

230 Figure 4 shows the model resolution of each array. R may be viewed as a filter that blurs
231 the true values of the subsurface resistivities (Stummer et al., 2004). To ensure a fair comparison
232 of R between the arrays of our test, the model discretization and all model constraints were kept
233 constant. Inverse model grid discretization included a 3m width in the horizontal direction and
234 variable layering from 1.1 to 8.5m. Constraints included using the L2 norm, initial model
235 dampening factor of 0.15, and increasing by a factor of 1.1 with depth. When evaluating results,
236 Fig. 4 shows that the model resolution is highest for the dipole-dipole array and the lowest for the
237 pole-pole array. For example, the average depth for the 0.063 isopleth (or log value of -1.2) is
238 6.8m, 7.7m, and 8.2m for pole-pole, Schlumberger, and dipole-dipole arrays, respectively. Table
239 1 lists several other statistics for the models to allow for direct comparison between them. Of the
240 three standard arrays tested, the dipole-dipole has the highest average resolution of 0.111.

241

242

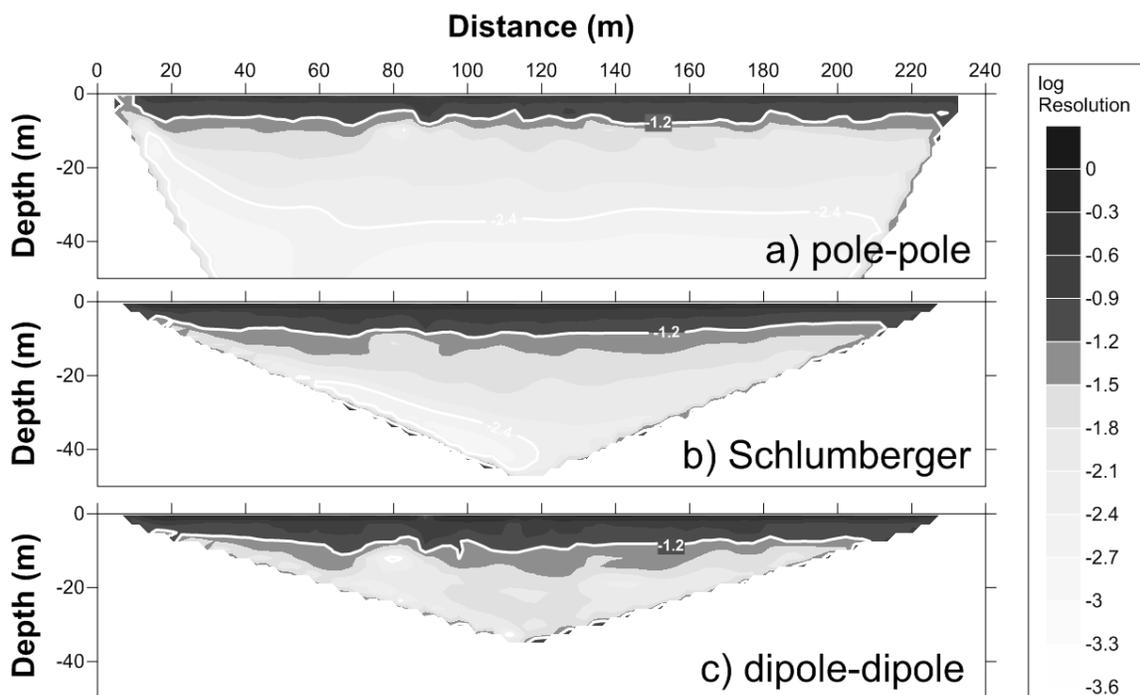
243

244

245

246

247 **Figure 4. Model resolution for a) pole-pole, b) Schlumberger, and c) dipole-dipole arrays.**



248

249 **Table 1. Resistivity and resolution statistics from inversion models**

Array	Resistivity Range (ohm-m)	Avg. Resolution	Avg. Depth for resolution isopleth = 0.063 (m)
Pole-pole	22.2-2787	0.042	6.8
Schlumberger	13.9-3007	0.096	7.7
Dipole-dipole	8.5-2674	0.111	8.2
Random with inner dipoles	11.4-5380	0.120	8.8
Random with outer dipoles	6.6-5859	0.117	9.1
Random with overlapping dipoles	19.6-8563	0.098	8.7
Random with all dipoles	12.8-6220	0.107	9.1
Optimum	8.5-5038	0.140	11.2

250

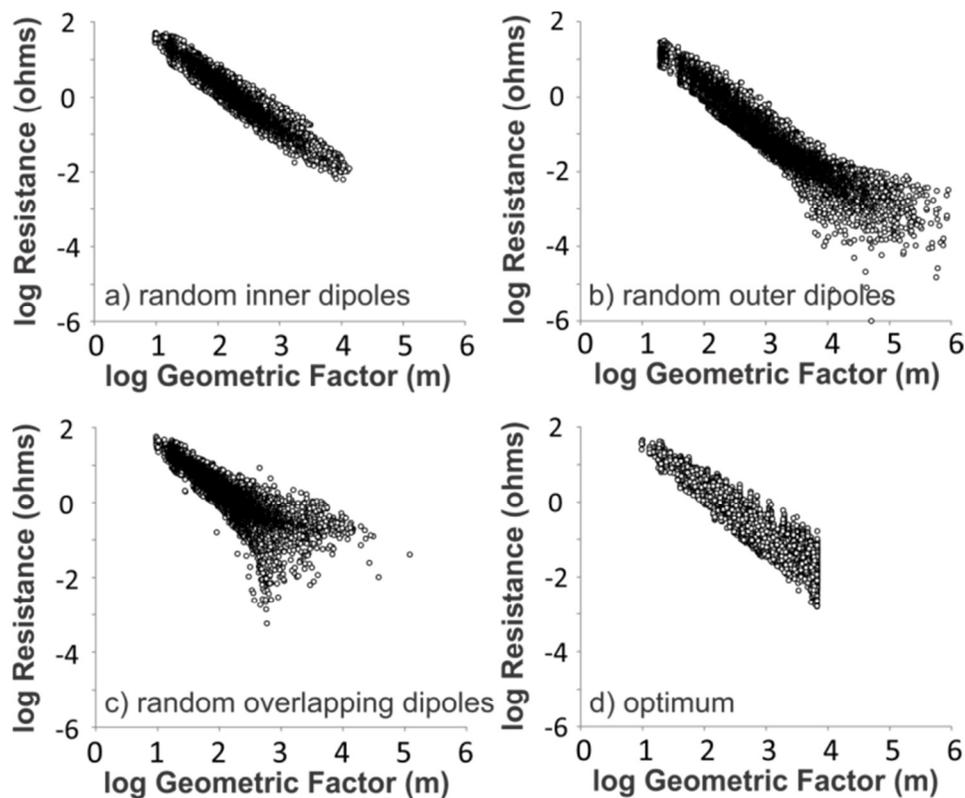
251 Random Arrays

252 The next test was to create a random set of 4-pole data from the 2-pole data. The
 253 algorithm for the randomized array first created a unique list comprising four integers that
 254 incorporated the 78 electrodes. A lookup function then combed the 2-pole dataset for the
 255 combinations associated with the random list and calculated the resistances according to Equation
 256 (1). In addition, the geometric factor (K) was calculated as:

$$257 \quad K = 2\pi \left(\left| \frac{1}{AM} \right| - \left| \frac{1}{AN} \right| - \left| \frac{1}{BM} \right| + \left| \frac{1}{BN} \right| \right)^{-1} \quad (3)$$

258 where distances between electrodes A, B, M, and N were used in the formulation. According to
 259 Xu and Noel (1993) and Rucker et al. (2011), we would expect the total number of 4-pole
 260 combinations from a 78-electrode dataset to be in excess of 4.2×10^6 . In this example we chose to
 261 limit our random set to 5×10^4 combinations and positive geometric factors less than 1×10^6 m.
 262 Furthermore, the random combinations were divided into inner dipoles, outer dipoles, and
 263 overlapping dipoles. Carpenter and Habberjam (1956) referred to these combinations as Alpha,
 264 Beta, and Gamma arrangements, respectively. The Wenner and Schlumberger arrays would be
 265 considered inner dipole arrangements and the dipole-dipole would be considered an outer dipole
 266 arrangement. Overlapping dipoles are constructed from transmitting electrode pairs straddling or
 267 interleaving the receiving electrodes. Figure 5 shows the distribution of these random data as
 268 resistance versus K. The data are shown to align along a fairly narrow band of apparent resistivity
 269 values, especially the inner dipole set of Fig. 5(a). The data from outer dipoles (Fig. 5(b)) span a
 270 much broader range of geometric factors and the data from overlapping dipoles (Fig. 5(c)) show
 271 fairly noisy resistance values at smaller K.

272 **Figure 5. Resistance versus geometric factor for random and optimum 4-pole combinations**
 273 **calculated form the 2-pole dataset. The random data are segregated by inner, outer, and**
 274 **overlapping dipoles.**



275

276

277

278 The individual and combined random dipole models were created using a subset of 4,100
279 and 5,400 resistance records, extracted for each dipole dataset, respectively. The dataset for each
280 model was based on those measurements with the lowest calculated noise according to Equation
281 (2). Using superposition, the repeat errors for each 2-pole combination, as provided from the
282 instrument data file, were added and an error value less than 1.5% was used as the cut-off in
283 developing the final model input file. Each dataset was inverted using similar parameters and
284 discretized grid as the standard arrays. The only exception was choosing to invert apparent
285 resistivity and not logarithm of apparent resistivity for the two examples that included
286 overlapping dipole data because negative apparent resistivities being calculated in the code
287 cannot be log transformed. The negative apparent resistivity was likely due to the differences in
288 the way geometric factor is calculated, which could have become negative in the inversion code.
289 Each random array converged to an RMS value less than 5% within four iterations.

290 The contours of resistivity in the random dipole models (Fig. 6) show a similar low
291 resistivity target among all models and with those of Fig. 3. The models of overlapping dipoles,
292 whether alone (Fig. 6(c)) or together with other dipoles (Fig. 6(d)) show a dampened target from
293 the choice of how the apparent resistivity data were used. However, the overlapping dipoles show
294 a deeper investigation depth. The resolution contours of Fig. 7 show subtle differences among the
295 models, but Table 1 shows the inner dipole model having the highest average resolution.

296 Optimized Array

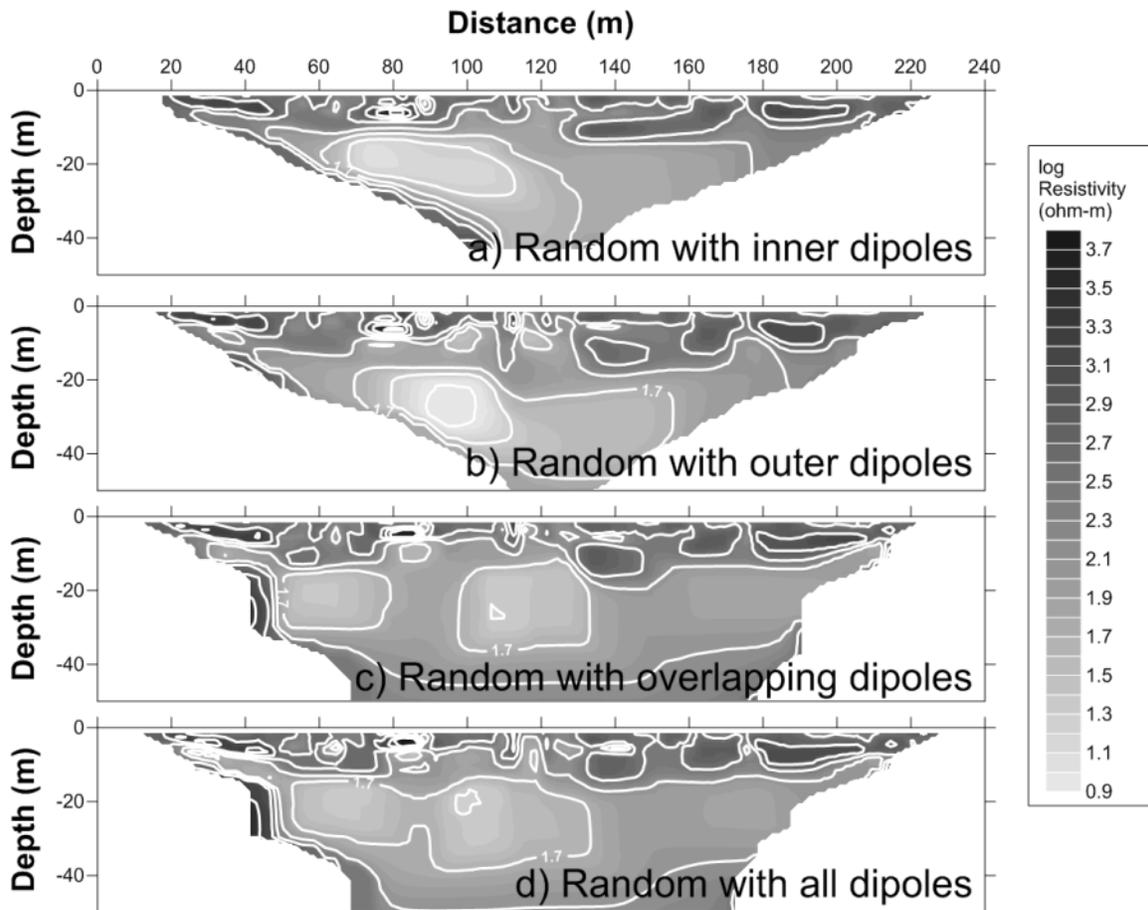
297 The last test was to create an optimal array comprising 4-pole combinations calculated from the
298 base 2-pole dataset. The Compare R method was used to calculate 8000 optimized pairs using the
299 dipole-dipole array as the base set. From Equation (1) the resistance was calculated for each
300 combination of the optimal array and Fig. 5(d) shows the distribution of resistance data versus
301 geometric factor after filtering to remove obvious outliers. After filtering, using similar criteria as
302 established for the randomly generated array, the final dataset for inverse modeling of the
303 optimized dataset comprised 4820 values.

304 Figure 8 shows the resistivity and resolution results for the optimal array. Again, to ensure
305 consistency among the models, the same model grid and inverse model parameters were used to
306 create Fig. 8. The resistivity data show the same low resistivity, high amplitude target at a depth
307 of 20 m as all other models with slight differences with respect to shape and extent across the
308 profile. For example, the isopleth for a log resistivity value of 1.7 is shown to have separated at a
309 distance of 130m. The model resolution is shown to be higher than all other arrays, with an
310 average value of 0.14 and the average depth to the 0.063 isopleth at 11.2m. This depth is 3m
311 below that of the dipole-dipole array and shows the power of using an optimized array to resolve
312 pertinent features of the subsurface.

313

314

315 **Figure 6. Inverse model results using randomly generated dipoles, segregated by a) inner**
316 **dipoles, b) outer dipoles, c) overlapping dipoles, and d) all dipoles.**



317

318

319

320

321

322

323

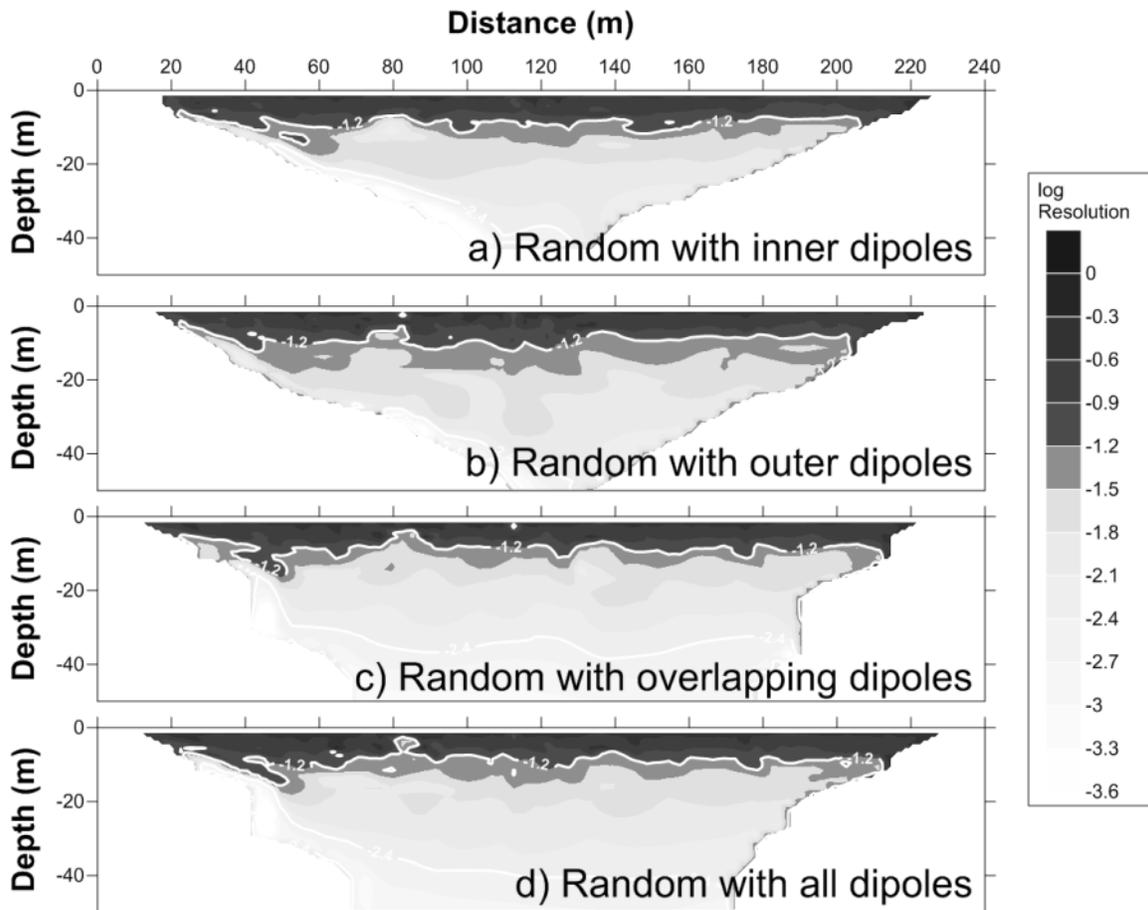
324

325

326

327

328 **Figure 7. Model resolution from randomly generated dipoles, segregated by a) inner**
 329 **dipoles, b) outer dipoles, c) overlapping dipoles, and d) all dipoles.**



330

331

332

333

334

335

336

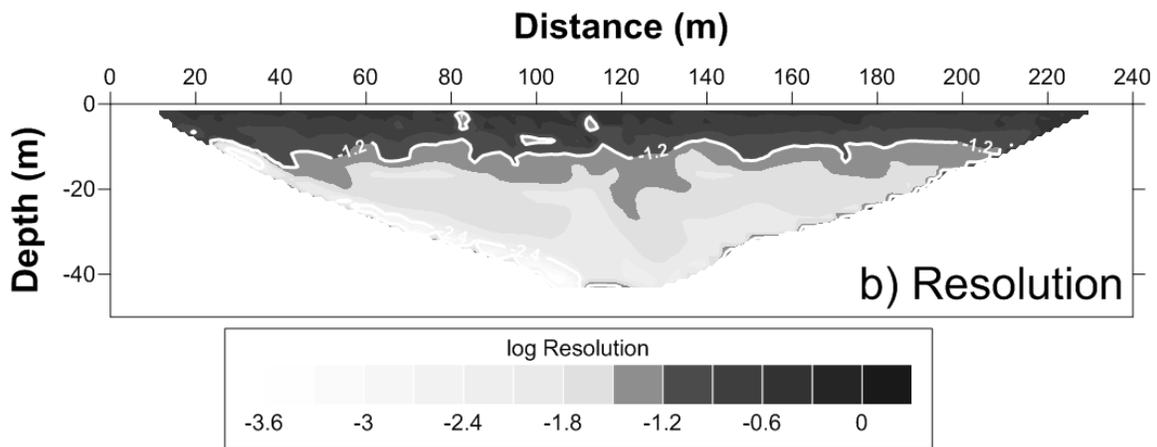
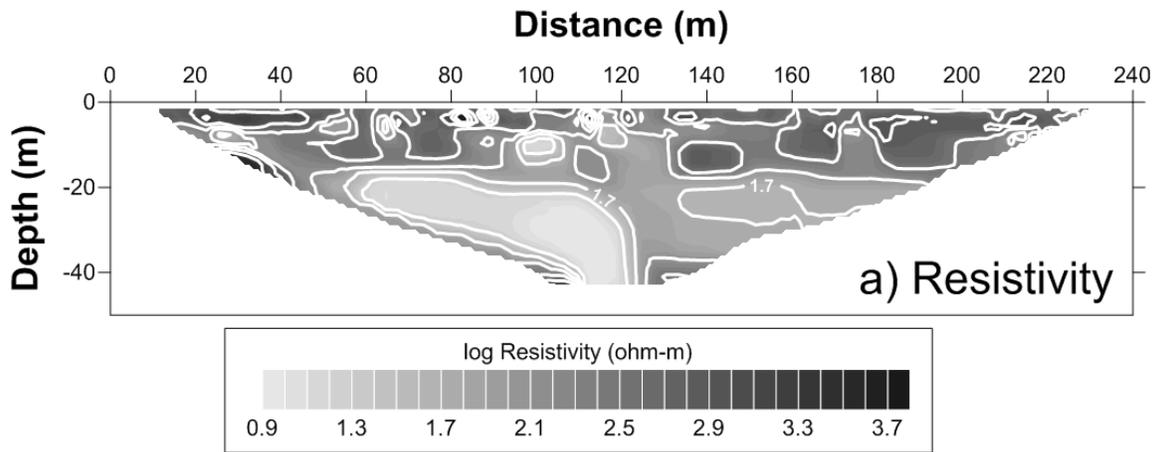
337

338

339

340

341 **Figure 8. Resistivity and resolution for the optimal array**



342

343

344

Conclusions

345 Evaluating different geometric arrays to maximize target recognition is rather popular in
 346 electrical resistivity investigations. Often, competing arrays such as the dipole-dipole,
 347 Schlumberger, gradient, and other standard configurations are collected simultaneously and
 348 modeled together or separately to compare the fidelity of the target's dimensions and resistivity
 349 amplitude. To ensure completeness of the study, multiple geological scenarios are usually
 350 surveyed and the best array is chosen based on the particular needs of the geophysicist. In this
 351 work, we also investigate multiple arrays to test their ability to recreate a hydrogeological target
 352 developed from disposal of sodium nitrate waste into a series of infiltration trenches. However,
 353 we take a slightly different tack by comparing nonstandard arrays reconstructed (i.e., calculated)
 354 from a base set of pole-pole data. The reconstruction linearly combines a series of four 2-pole
 355 arrangements to form any desired 4-pole arrangement.

356 In the first step, we compared the reconstruction of resistance data from the standard
 357 arrays of dipole-dipole and Schlumberger to measured data of the same array. The pole-pole array
 358 is known for having a high S/N and the reconstruction using 2-pole data showed to be equivalent
 359 to and in a few cases superior to the measured array in terms of noise. Inverse models were then

360 generated for each array to understand the resolving capabilities of the different measurements.
361 The dipole-dipole array was shown to have the highest model resolution based on the statistics
362 from the resolution matrix compared to the Schlumberger and pole-pole arrays. As a general
363 observation, it appears that those arrays with the shallowest depth of investigation have higher
364 average model resolution.

365 In the next set of tests, we generated random 4-pole combinations that comprised
366 approximately a third each of inner dipoles, outer dipoles, and overlapping dipoles. These dipoles
367 are equivalent to the Alpha, Beta, and Gamma arrangements, respectively. The resistance data
368 from each type of dipole were plotted against the geometric factor and the inner dipole data was
369 shown to align along a fairly narrow band of apparent resistivity values. The outer and
370 overlapping dipole data had greater amounts of noise with a larger spread in apparent resistivity
371 at larger geometric factors. Inverse models showed that the inner and outer dipoles could
372 reconstruct the nitrate target with similar resistivity attributes as standard arrays but the model
373 resolution was slightly higher. The higher resolution could be simply from more resistance data
374 being used in the random sets. The models using overlapping dipoles were slightly unstable and
375 the model resolution from them was lower than the dipole-dipole array.

376 Lastly, a 4-pole optimized array was reconstructed from the 2-pole dataset. The
377 optimization algorithm was based on explicitly increasing the values along the diagonal of the
378 model resolution matrix using the Compare R method. The method searches for combinations
379 that increase the resolution and rejects combinations that decrease the resolution. One constraint
380 of the search criteria was to not consider overlapping dipoles based on their instability in
381 modeling. The reconstructed optimized resistance data were shown to also align along a fairly
382 narrow band of apparent resistivity values. The resistivity inverse model showed a familiar target
383 as other arrays with slightly more detail. The model resolution was shown to be higher than all
384 other arrays, thus demonstrating that very little effort is needed in acquiring a high quality dataset
385 with low noise and creating a resistivity model with a much better resolvability than what is
386 usually measured. The technique presented herein would seem to be highly advantageous when
387 considering time lapse resistivity monitoring, where low sampling time and high model resolution
388 are competing factors in the survey design.

389

References

- 390 Al Hagrey, S.A., 2012, 2D Optimized electrode arrays for borehole resistivity tomography and
391 CO₂ sequestration modelling: *Pure and Applied Geophysics*, **169**, 1283–1292
- 392 Batayneh, A.W., 2001, Resistivity imaging for near-surface resistive dyke using two-dimensional
393 DC resistivity techniques: *Journal of Applied Geophysics*, **48**,25–32.
- 394 Blome, M., Maurer, H., Greenhalgh, S., 2011, Geoelectric experimental design—Efficient
395 acquisition and exploitation of complete pole-bipole data sets: *Geophysics*, **76**, F15–F26.

- 396 Candansayar, M.E. and Basokur, T., 2001, Detecting small-scale targets by the 2D inversion of
397 two-sided three-electrode data: application to an archaeological survey. *Geophysical*
398 *Prospecting*, **49**, 13–25.
- 399 Carpenter, E.W. and Habberjam, G.M., 1956, A tri-potential method of resistivity prospecting,
400 *Geophysics*, **21**, 455–469.
- 401 Dahlin, T. and Zhou, B., 2004, A numerical comparison of 2D resistivity imaging with 10
402 electrode arrays: *Geophysical Prospecting*, **52**, 379–398.
- 403 Dey, A., Meyer, W.H., Morrison, H.F., and Dolan, W.M., 1975, Electrical field response of two-
404 dimensional inhomogeneities to unipolar and bipolar electrode configurations. *Geophysics*,
405 **40**, 630–640.
- 406 Gee, G.W., Oostrom, M., Freshley, M.D., Rockhold, M.L., and Zachara, J.M., 2007, Hanford site
407 vadose zone studies: An overview: *Vadose Zone Journal*, **6**, 899.
- 408 Kaufmann, O., Quinif, Y., 2001, An application of cone penetration tests and combined array 2D
409 electrical resistivity tomography to delineate cover-collapse sinkholes prone areas: In Beck,
410 B.F., Herring, J.G. (Eds.), *Geotechnical and Environmental Applications of Karst Geology*
411 *and Hydrology*. Balkema, Lisse, pp. 359–364.
- 412 Lehmann, H., 1995, Potential representation by independent configurations on a multi-electrode
413 array: *Geophysical Journal International*, **120**, 331–338.
- 414 Lindenmeier, C.W., Serne, R.J., Bjornstad, B.N., Last, G.V., Lanigan, D.C., Lindberg, M.J.,
415 2002, Characterization of Vadose Zone Sediment: Borehole C3103 Located in the 216-B-7A
416 Crib Near the B Tank Farm, PNNL-14128: Pacific Northwest National Laboratory, Richland,
417 WA.
- 418 Leontarakis, K. and Apostolopoulos, G.V., 2012, Laboratory study of the cross-hole resistivity
419 tomography: The Model Stacking (MOST) Technique: *Journal of Applied Geophysics*, **80**,
420 67–82.
- 421 Loke, M.H., Wilkinson, P.B., & Chambers, J.E., 2010a, Fast computation of optimized electrode
422 arrays for 2D resistivity surveys: *Computers & Geosciences*, **36**, 1414–1426.
- 423 Loke, M.H., Wilkinson, P.B., and Chambers, J.E., 2010b, Parallel computation of optimized
424 arrays or 2-D electrical imaging surveys: *Geophysical Journal International*, **183**, 1302–1315.

- 425 Loke, M.H., Chambers, J.E., Rucker, D.F., Kuras, O., and Wilkinson, P.B., 2013, New
426 developments in the direct-current geoelectrical imaging method. *Journal of Applied*
427 *Geophysics*, **95**, 135–156.
- 428 Loke, M.H., Wilkinson, P.B., and Chambers, J.E., Strutt, M., 2014. Optimized arrays for 2D
429 cross-borehole electrical tomography surveys: *Geophysical Prospecting*, **62**, 172–189.
- 430 Maurer, H., Boerner, D.E., and Curtis, A., 2000, Design strategies for electromagnetic
431 geophysical surveys: *Inverse Problems*, **16**, 1097–1117.
- 432 Menke, W., 1984, *Geophysical data analysis: Discrete Inverse Theory*, Academic Press, London.
- 433 Rucker, D.F., J.B. Fink, and M.H. Loke, 2011, Environmental monitoring of leaks using time
434 lapsed long electrode electrical resistivity: *Journal of Applied Geophysics*, **74**, 242–254.
- 435 Rucker, D.F., 2012, Enhanced resolution for long electrode ERT: *Geophysical Journal*
436 *International*, **191**, 101–111.
- 437 Rucker, D.F., Myers, D.A., Cabbage, B.D., Levitt, M.T., Noonan, G.E., McNeill, M., Henderson,
438 C., and Lober, R.W., 2013, Surface Geophysical Exploration: Developing Noninvasive Tools
439 to Monitor Past Leaks around Hanford’s Tank Farms: *Environmental Monitoring and*
440 *Assessment*, **185**, 995–1010.
- 441 Saydam, A.S. and Duckworth, K., 1978, Comparison of some electrode arrays for their IP and
442 apparent resistivity responses over a sheet like target: *Geoexploration*, **16**, 267–289.
- 443 Seaton, W.J. and Burbey, T.J., 2002, Evaluation of two-dimensional resistivity methods in a
444 fractured crystalline-rock terrane: *Journal of Applied Geophysics*, **51**, 21–41.
- 445 Sri Niwas and Israil, M., 1989, Matrix Method for the Transformation of Resistivity Sounding
446 Data of One Electrode Configuration to that of another Configuration: *Geophysical*
447 *Prospecting*, **37**, 209–221.
- 448 Stummer, P., Maurer, H., and Green, A., 2004, Experimental design: electrical resistivity data
449 sets that provide optimum subsurface information: *Geophysics*, **69**, 120–129.
- 450 Wilkinson, P.B., Meldrum, P.I., Chambers, J.E., Kuras O., and Ogilvy, R.D., 2006, Improved
451 strategies for the automatic selection of optimized sets of electrical resistivity tomography
452 measurement configurations: *Geophysical Journal International*, **167**, 1119–1126.
- 453 Wilkinson, P.B., Loke, M.H., Meldrum, P.I., Chambers, J.E., Kuras, O., Gunn, D.A., and Ogilvy,
454 R.D., 2012, Practical aspects of applied optimized survey design for electrical resistivity
455 tomography. *Geophysical Journal International*, **189**, 428–440.
- 456 Xu, B., and Noel, M., 1993, On the completeness of data sets with multielectrode systems for
457 electrical resistivity surveys: *Geophysical Prospecting*, **41**, 791–801.
- 458 Zhou, W., Beck, B.F., and Adams, A.L., 2002, Effective electrode array in mapping karst hazards
459 in electrical resistivity tomography: *Environmental Geology*, **42**, 922–928.