Influences on Shallow Ground Temperatures in High Flux Thermal Systems

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Abstract

Ground temperature measurements are a useful indication of subsurface processes and heat flux, particularly in volcanic and hydrothermal systems, but obtaining reliable data at sufficient resolution can be difficult. Investigators commonly use temperature measurements at 1 meter depths to minimize land surface boundary impacts; however, these measurements are time-consuming and invasive, limiting the number of points that can be surveyed. Alternatively, shallow ground temperature measurements (≤ 25 cm depth) offer a rapid and minimally-invasive way to collect a large number of observations in a target area. Although this method has obvious appeal, changing atmospheric conditions can impact the observed temperatures, and thus may reasonably be expected to influence interpretations arising from the data. Here we examine the impact of precipitation and changing air temperature on shallow ground temperatures in the vicinity of a group of hot springs located in Yellowstone National Park, Wyoming. We find that the mean, the range, and the skewness of the observed temperatures were decreased by changing atmospheric conditions; however, the model variogram representing data taken after several days of moderate precipitation adequately described the spatial correlation of data taken before precipitation. We therefore conclude that the ability to differentiate between high- and low-flux areas may be somewhat reduced by moderate precipitation and changing atmospheric conditions, but that interpretations made on the basis of characteristics of the inferred variograms are likely to be robust to such perturbations in high heat flux environments.

Keywords: ground temperatures, hydrothermal springs, Yellowstone caldera, geostatistics, correlation structure

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1. Introduction

Ground temperatures are an inexpensive, versatile, and widely used approach to the investigation of shallow subsurface processes. In the earth and environmental sciences they are often applied to the study of volcanic and/or geothermal systems; for example, they have been used to estimate geothermal heat fluxes (Dawson, 1964; Sorey and Colvard, 1994; Ingebritsen et al., 2001; Hurwitz et al., 2012), to track the development of a geothermal field after a volcanic eruption (Saba et al., 2007), to determine patterns of hydrothermal manifestations on an active volcano (Miller and Mazot, 2013), and to examine structural controls on hydrothermal systems (Anderson and Fairley, 2008; Rissmann et al., 2011). Outside of geothermal and volcanic systems ground temperature measurements have been used to analyze heat transfer in forested valley regions (Kawanishi, 1983), assess slope failure from shallow groundwater (Furuya et al., 2006), and in studies of the relationship between seismic noise and ground temperature (Gordeev et al., 1992). Near surface temperature fields have even been applied to archaeological studies; for example, Mori et al. (1999) showed that diurnal ground temperature changes at the Kirui-Otsuka mounded tomb were quantitatively different over the central burial mound in comparison to sites remote from the tomb. Ground temperature measurements have also featured prominently in studies of fault permeability (Fairley and Hinds, 2004b; Fairley, 2009) and fault-controlled hydrothermal circulation (Fairley and Hinds, 2004a).

The majority of ground temperature studies rely on measurements at depths of about 1 m. This depth is chosen to minimize the influence of changing atmospheric conditions—particularly diurnal temperature variations—and arises from the well-known result that the amplitude of periodic temperature variation decreases with depth according to (Carslaw and Jaeger, 1959):

$$A(z) \propto A(z = 0) \exp \left(-z \sqrt{\frac{\omega}{2D}} \right), \quad (1)$$

where z is the depth below landsurface [L], A is the amplitude of temperature variation at depth z , D is the soil thermal diffusivity [L^2/T], and ω is the angular frequency [$2\pi/\text{T}$]. For a soil with thermal diffusivity of $10^{-6} \text{ m}^2/\text{s}$, the amplitude of diurnal temperature changes should therefore have decayed to less than 1% at a depth of 1 m.

The idea of limiting atmospheric influence on measured temperatures is attractive; however, other considerations weigh against such methods. Perhaps most important is that digging or augering a 1 m deep hole requires a considerable investment of time and effort, and the resulting thermal perturbation must dissipate prior to obtaining a representative temperature measurement. Furthermore, these observations are relatively intrusive, and may be frowned upon or even prohibited in sensitive areas (e.g., national parks, wilderness areas). Because of the time- and labor-intensive nature of 1 m depth measurements, there is a limit to the number of points that can be obtained, and data collection may be restricted in some areas.

In an effort to circumvent some of the more restrictive aspects of 1 m deep temperature measurements, some researchers have used ground temperature observations from shallower depths, typically in the range of 15–25 cm. The use of shallow temperature surveys was pioneered by Dawson (1964), who developed an empirical relationship between shallow (15 cm) ground temperature measurements and heat flow through soils in the Wairakei hydrothermal system in New Zealand. The investigator recommended the use of 1 m depth temperature measurements for relatively low heat flow areas in which heat transfer is dominated by conduction, citing the work of Thompson (1960). In higher heat flow areas dominated by convective heat transfer, the investigator proposed the use of temperature measurements at a depth of 15 cm, and gave an empirical formula relating heat flow, H (in units of $\text{cal}/\text{m}^2\text{s}$), to the temperature in degrees Celsius at 15 cm depth (T_{15}) (Dawson, 1964):

$$H = 1.24T_{15}^4 \times 10^6. \quad (2)$$

The Dawson (1964) formula (i.e., Equation 2) was later modified to account for the effects of elevation by Sorey and Colvard (1994) for use in Lassen Volcanic National Park (Ingebritsen et al., 2001), where those investigators developed a comprehensive heat flow budget for the Lassen volcanic system.

More recently, some investigators have favored shallow (≤ 25 cm) ground temperature measurements for investigations in geothermal areas because the shallow depth of penetration and short equilibration times allow the collection of hundreds or thousands of data points in a day (e.g., Fairley and Hinds, 2004a,b; Heffner and Fairley, 2006; Anderson and Fairley, 2008). The cited studies reported measurements at high resolutions (generally between 1×1 to 5×5 m spacing) over domains ranging up to 100×800 m. These relatively large, spatially-referenced and high-resolution data sets may be useful

101 for developing spatial-statistical representations of the underlying generating
102 process(es) (Anderson and Fairley, 2008), or inferring aspects of the near-
103 subsurface fluid flow paths (Fairley and Hinds, 2004a; Fairley and Nicholson,
104 2006). In addition, the method is minimally invasive, and may often be al-
105 lowed in areas where the augering of even a few 1 m deep holes would be
106 prohibited.

107 In spite of the obvious attractions of shallow temperature surveys, the
108 fact that changing atmospheric conditions perturb subsurface temperatures
109 raises questions about the robustness of inferences made on the basis of shal-
110 low temperature measurements. In the present study, our goal is to examine
111 the extent to which patterns of shallow ground temperatures are impacted
112 by precipitation and changing atmospheric conditions in an area of relatively
113 high heat flux, located in the Morning Mist Springs area of the Yellowstone
114 caldera. We find that changing environmental conditions in our study area
115 reduced the mean and the range of measured temperatures, as well as de-
116 creasing the skewness of the measured data. However, an analysis of kriging
117 residuals before and after a series of precipitation events demonstrated that
118 the model variogram representing the shallow temperature distribution was
119 not particularly sensitive to variations in the surface boundary condition.

120 2. Site Description

121 The study area is located in Yellowstone National Park, northwestern
122 Wyoming (Figure 1). The Park is located in the Yellowstone Plateau Vol-
123 canic Field (YPVF), which is part of the most recent string of large calderas
124 formed along the Snake River Plain over the past 17 million years (Pierce
125 and Morgan, 1992; Hurwitz and Lowenstern, 2014) from the migration of the
126 North American Plate over the Yellowstone hot spot (Pierce and Morgan,
127 1992; Love et al., 2007). The YPVF is home to a large hydrothermal system,
128 the surface expression of which comprises over 10,000 hydrothermal features,
129 including fumaroles, geysers, mud pots, thermal springs, and hydrothermal
130 explosion craters (Hurwitz and Lowenstern, 2014). Almost all of the heat,
131 and a considerable fraction of the noncondensable gases, discharged on the
132 YPVF are derived from the underlying magmatic source and transported
133 through the shallow hydrothermal system (Hurwitz and Lowenstern, 2014;
134 Lowenstern et al., 2015).

135 The present study took place in the Lower Geyser Basin, near the western
136 entrance to the Park. We measured spring and shallow ground temperatures

Figure 1: Location map of the study area. The study area is one kilometer along the Mary Mountain Trail from the trailhead on Route 287 in Yellowstone National Park. The approximate location of the study area within the Park is marked by a star on the inset.

137 in the vicinity of spring LCBNN159 (Rodman and Guiles, 2008), which is ac-
138 tually a group of six small thermal springs (one main spring and five smaller,
139 subsidiary springs) located about 60 m off the Mary Mountain/Nez Perce
140 Creek Trail, about 1 km east of the trailhead on Highway 287 (Figure 1).
141 The springs are positioned in a large, open meadow, just to the north of a
142 line of small hills, in an area of sparse vegetation that is consistent with a
143 high conductive heat flux. Surficial deposits in the area consist of white to
144 light brownish-gray diatomaceous silt deposited in flat, marshy areas (Muf-
145 fler et al., 1982); away from the thermal springs, surficial deposits consist
146 of gray to light brown, moderately- to well-sorted unconsolidated sands and
147 gravels interpreted to be outwash from the Pinedale glaciation (Muffler et al.,
148 1982). Details of the regional geology are given in Pierce and Morgan (1992)
149 and Love et al. (2007). The Yellowstone hydrothermal system is described
150 in Hurwitz and Lowenstern (2014), and the geology specific to the study site
151 is summarized in Lubenow (2015).

152 **3. Methods and Analysis**

153 *3.1. Data Collection*

154 We measured ground temperatures in a 72×72 m area, with the main
155 spring LCBNN159 approximately centered in the grid. For identification
156 purposes we called the grid “Bravo” to differentiate it from other temperature
157 grids in the same area (Lubenow, 2015). The study area’s small spatial
158 extent allowed a high density of temperature measurements, with the goal
159 of identifying the variability of conductive heat fluxes in the near-field of
160 spring LCBNN159. The Bravo grids were measured on a 3×3 m spacing, for
161 a nominal total of 625 points.

162 Temperature measurements were made with Fluke 51 II single input dig-
163 ital thermometers, having a reported accuracy of $\pm 0.05\% + 0.3^\circ\text{C}$. Each
164 thermometer was paired with an Omega Rugged Penetration Thermocouple
165 Probe (K-type) with a “T” handle. The probes are 20 cm in length and 6.4
166 mm in diameter, and are armored to penetrate dense or compacted soils. A
167 plane table/alidade and stadia rod were used to stake out the grid, which
168 was demarcated with 100 m fiberglass surveyor’s chains (tapes). In addition,
169 we probed each spring in the grid using a Fluke 51 II digital thermometer
170 paired with a Digi-Sense K-type standard thermocouple probe, having a 12.7
171 cm length and a 2.4 mm diameter tip. Multiple measurements were made

172 on each spring to establish the highest repeatable temperature; temperatures
173 for springs located within the Bravo grid ranged from 26.3–76.7°C.

174 To ensure high-quality, reproducible measurements, all probe/thermometer
175 pairs were calibrated in ice- and boiling-water baths before the start of field-
176 work, and checked for drift by immersion in ice water at the conclusion of
177 each day’s activity. In addition, probe/thermometer pairs were simultane-
178 ously subjected to periodic “air temperature checks,” in which all probes were
179 removed from the ground and allowed to equilibrate with the ambient (air)
180 temperature. These checks were performed before starting a temperature
181 grid, after finishing a grid, and at least three times during the data collec-
182 tion to identify any probe/thermometer combinations that showed anomalous
183 readings; any pairs not functioning properly were immediately exchanged for
184 a correctly functioning pair.

185 To maximize efficiency while collecting ground temperature data (and
186 thus minimize the time required to complete any individual grid), we used
187 sets of probe/thermometer pairs to collect 12 or 13 data points simultane-
188 ously. Lines of probe/thermometer pairs were moved in 3 m increments to
189 collect one-half the total data points in the grid, then the line was reversed,
190 and the other half of the points were acquired. Working in this way, an
191 entire temperature grid could be completed in under four hours, minimizing
192 the effects of changing atmospheric conditions on the data.

193 Data were collected for the first Bravo grid (“Bravo”) on 25 June, 2014.
194 A resurvey of the Bravo grid (“2Bravo”) was completed three days later, on
195 28 June, 2014. At a few locations, temperatures could not be taken due
196 to the presence of hydrothermal precipitate (sinter). As a result, the Bravo
197 dataset consists of 610 shallow ground temperature measurements (15 drop-
198 outs, or about 2.5% of the total grid), while the 2Bravo dataset consists
199 of 616 measurements (9 drop-outs, or about 1.4% of the total grid). The
200 locations of the missing data points are presented in Figure 2. Kriged plots
201 of spring locations and shallow ground temperatures for both the Bravo and
202 2Bravo surveys are shown in Figure 3. A complete discussion of the data
203 collection for the Bravo grids, including methods used to ensure accurate
204 and reproducible data collection, is available in Lubenow (2015).

205 3.2. Data Analysis

206 Summary statistics (mean, median, variance, etc.) for the ground and
207 spring temperatures were calculated with the statistical computing program
208 “R” (R Development Core Team, 2008). Summary statistics for the data sets

Figure 2: Locations of missing data points for the Bravo (filled circles) and 2Bravo (open circles) data sets.

Figure 3: Ground temperatures before and after precipitation, kriged onto a 0.25×0.25 m grid. a) Bravo grid, b) 2Bravo grid. The locations of the springs within the grid are marked by circles. The main spring, LCBNN159, is marked with a filled circle; the smaller, subsidiary springs are marked with open circles.

Figure 4: Frequency histograms of temperatures in the (a) Bravo and (b) 2Bravo data sets. Bin size is 2.0°C.

Table 1: Summary statistics for spring temperatures, Bravo, and 2Bravo ground temperature grids. N is the number of measurements in the indicated data set; NA is the number of missing points. All temperatures given in °C.

	Min	1 st Q	Median	Mean	3 rd Q	Max	StDev	N	NAs
Springs	26.30	44.55	49.80	49.27	50.50	76.70	14.91	7	-
Bravo	14.90	16.90	18.90	19.58	21.40	33.50	3.40	610	15
2Bravo	9.50	14.20	16.00	16.11	17.90	26.70	2.54	616	9

are given in Table 1, and histograms of the Bravo and 2Bravo temperatures are shown in Figure 4. After estimating summary statistics and plotting the ground temperature data to check for obvious outliers or erroneous data points, we made a point-by-point comparison between the two data sets to obtain an understanding of how the changing atmospheric conditions impacted the surface expression of the shallow temperature field. For this comparison, we subtracted from each point in the Bravo data set the value of the temperature at the corresponding point in the 2Bravo data set; the resulting map of temperature differences is shown in Figure 5.

In addition to the direct comparison of temperatures, we wanted to assess the influence of the boundary condition changes on the correlation structure (the shape and parameterization of the variogram) that described the shallow temperature distribution. The ground and spring temperatures were analyzed separately, under the assumption that the two types of data derived from different generating mechanisms; i.e., the spring temperatures resulted from pure advective heat transport, while the ground temperatures

Figure 5: Map-view plot showing the temperature differences between the Bravo and 2Bravo data sets, where the temperature difference is calculated as $\Delta T = T_{\text{Bravo}}(x, y) - T_{2\text{Bravo}}(x, y)$. Contour interval is 2°C.

225 arose primarily from conductive heat transfer. After separating the ground
 226 and spring temperature data sets, we developed a “model variogram” for the
 227 2Bravo data. A model variogram is a mathematical quantification of the spa-
 228 tial correlation structure; that is, the model variogram quantifies the amount
 229 of information carried by a measured data point about the value of another,
 230 unsampled point, located some distance h away from the sampled one. The
 231 model was constructed following a standard geostatistical approach to the
 232 analysis of spatial data, using the well-known GSLIB software suite (Deutsch
 233 and Journel, 1998). Initially the data were checked for marked anisotropy by
 234 plotting a variogram map, after which experimental (data-based) variograms
 235 for various combinations of lags were developed with the GSLIB routine `gamv`,
 236 and were modeled to arrive at a satisfactory mathematical description of the
 237 generating process. An experimental variogram is defined as (Deutsch and
 238 Journel, 1998):

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} (z_i - z_{i+h})^2, \quad (3)$$

239 where γ is the semivariance, h is the separation distance between data values

Table 2: Parameters for the model variogram of the 2Bravo data. The values for the partial sill are normalized such that the variance of the data is equal to one.

Model	Range (m)	Partial Sill
Nugget	-	0.21
Spherical	33.0	0.79

z_i and z_{i+h} , and $N(h)$ is the number of data pairs separated by distance h . Typically there are too few samples at any given separation distance to obtain a reliable estimate of γ for a given h . It is therefore traditional to segregate the data into a finite number of bins (or “lags”) and take the sum in Equation 3 over all the pairs in each bin. Experimental variograms are used to quantify the similarity (or dissimilarity) of a variable between two spatially-separated locations. The experimental variogram is fitted with a mathematical model (the model variogram) hypothesized to represent the correlation structure of the generating process responsible for the observed realization (the data). The model variogram is a superposition of acceptable (i.e., positive definite) models, commonly consisting of a “nugget” model that represents variability at a length scale smaller than the separation distance for the smallest lag, and one or more standard models of spatial correlation, e.g., exponential, Gaussian, power law. For the 2Bravo data, the spherical model, in combination with a nugget model, was found to be a good fit to the experimental variogram. The spherical model is defined as (Deutsch and Journel, 1998):

$$\gamma(h) = \begin{cases} c \cdot \left[1.5 \left(\frac{h}{a} \right) - 0.5 \left(\frac{h}{a} \right)^3 \right], & h \leq a, \\ c, & h > a, \end{cases} \quad (4)$$

where c is the partial sill (the contribution to the variance from the spherical model, where the remaining contribution to the variance is provided by the nugget), and a is the range (the separation distance beyond which points are uncorrelated). The parameters for the fitted model, with the sill values normalized to the variance of the data, are shown in Table 2, while a plot of the experimental and model variograms is shown in Figure 6.

After fitting a model variogram to the 2Bravo data, the model was checked using the cross-validation routine in the GSLIB kriging program `kt3d` (Deutsch and Journel, 1998). Cross-validation is a process for checking the appropriateness of a model variogram using a “leave-one-out” strategy, where one

Figure 6: Experimental (points) and model (line) variograms for the 2Bravo data. The semivariance has been normalized such that the variance of the data is equal to one.

267 data point is held back from the conditioning data set, and kriging is used to
268 estimate the missing point. The process is then repeated until all the data
269 points have been estimated. If the model is a reasonable representation of
270 the data, the residuals (the differences between the true and estimated values
271 of the data points) are expected to be unbiased (i.e., they should be approxi-
272 mately normally-distributed and have a mean not significantly different from
273 zero), have minimum variance, and be uncorrelated (e.g., they should be fit
274 by a pure nugget variogram) (Kitanidis, 1997). Because there are an infinite
275 number of possible variogram models that could fit the data, the requirement
276 for minimum variance is difficult to assess; however, the bias and correlation
277 of the residuals are relatively easy to assess. If the distribution of residu-
278 als diverges too strongly from expectations, the model variogram may be
279 reestimated or otherwise revised until a satisfactory model is identified.

280 Once an appropriate model variogram was found to represent the 2Bravo
281 data (Table 2), the same model was used with the cross-validation routine
282 of `kt3d` to estimate the values of the Bravo data set. The residuals were
283 again checked for uncorrelatedness, normal distribution, and zero mean. The
284 means, standard deviations, and standard errors of the kriging residuals for

Figure 7: Statistics of residuals from kriging cross-validation. a. Histogram of residuals from cross-validation of Bravo data set using the 2Bravo model variogram; b. QQ plot of residuals from cross-validation of Bravo data set using the 2Bravo model variogram; c. Histogram of residuals from cross-validation of 2Bravo data/model variogram; d. QQ plot of residuals from cross-validation of 2Bravo data/model variogram.

Table 3: Mean, standard deviation, standard error of the mean, and the mean square error of the residuals from the cross-validation of the Bravo and 2Bravo data sets. All values reported in °C.

Data	Mean	StDev	StErr	MSE
Bravo	0.0025	1.328	0.054	1.327
2Bravo	0.0006	1.477	0.060	1.458

the two data sets are shown in Table 3; histograms and QQ plots (i.e., the sample distribution plotted as a function of a theoretical normal distribution) of the residuals are reproduced in Figure 7.

4. Results and Discussion

As noted above, initial data collection for the Bravo grid took place on 25 June, 2014, after a period of settled weather during which there was little or no precipitation at the study area. Following collection of the Bravo data set, there was a significant lowering of air temperatures and an increase in precipitation in the vicinity of the study area. Although we do not have site-specific data for precipitation at the Bravo site, Table 4 provides mean daily precipitation totals for all meteorological stations within a 40 km radius of the study site, as well as specific daily measured precipitation amounts for the closest meteorological station, the Old Faithful Ranger Station, located 13 km from the site. The 2Bravo data set was collected after the 28 June precipitation event, with the intention of examining the influence of changing atmospheric conditions on shallow ground temperatures.

Air temperatures recorded in the vicinity of the Bravo grid exhibited diurnal fluctuations of around 20°C during the four days leading up to data collection on 25 June. Shortly after the initial Bravo grid data collection, a trend of cooling air temperatures (around 10°C on average) began, and continued over the following three days (Figure 8). Summary statistics for the two ground temperature grids (Table 1) show a parallel trend to the air temperatures, with all columns of Table 1 showing an obvious decline of 2.5 to 7°C between the Bravo and 2Bravo data gathering efforts. This overall decline in temperatures is also visible in the kriged temperature fields for the two data sets (Figure 3); however, the change in ground temperatures is expressed differently in the variogram analysis than in the direct comparison shown in Figure 5. The different impacts of the changing environmental

Table 4: Daily precipitation data in the vicinity of the study area. The mean and standard deviation are presented for all meteorological stations within a 40 km radius of the study area ($N = 5$), with the daily precipitation data for the closest station, Old Faithful Ranger Station (OFRS), located 13 km from the study area, presented for comparison purposes. Data provided by NOAA/NCEI.

Date (m.dd)	Mean (mm)	StDev (mm)	OFRS (mm)
6.20	0.50	1.118	0.00
6.21	1.02	2.281	0.00
6.22	0.50	1.118	0.00
6.23	0.66	1.085	0.80
6.24	1.26	1.337	0.00
6.25	0.60	1.084	0.00
6.26	4.48	4.722	1.00
6.27	3.60	2.523	2.00
6.28	7.94	2.430	11.70

conditions on these two methods of analysis, and the implications for interpreting perturbed temperature fields, are discussed in the following sections.

4.1. Direct Temperature Comparison

As was remarked earlier, the summary statistics in Table 1 show a decline in shallow ground temperatures of between 2.5 and 7°C for all of the categories included in the table. However, in addition to an overall lowering of temperatures (e.g., a lowering of the mean), the Bravo data have a greater positive (right-tailed) skew than the 2Bravo data; that is, the high temperature tail is greatly reduced in the 2Bravo data over the Bravo data (Figure 4). The impression that higher temperatures are more strongly affected by the changes in the surface boundary condition is reinforced by the results of the point-by-point differencing. Figure 5 clearly shows the greatest lowering of temperatures to be concentrated in two main areas and, by comparison with Figure 3, it can be seen that these two areas coincide closely with the areas of highest temperature in the Bravo data. In what follows, we assume the observed changes in shallow ground temperatures are primarily the result of perturbations to the upper boundary condition (i.e., the land-atmosphere boundary), and discuss three potential factors that could drive the observed behavior: a heat-sink effect from infiltrating precipitation, a change in the

Figure 8: Air temperature time-series data taken during the study described here. Times are given in hours from midnight (12:00AM) on 22 June, 2014. The approximate times at which temperature measurements were made for the Bravo and 2Bravo temperature grids are marked by gray bands.

333 far-field air temperature, and a change in the coefficient of convective heat
 334 transfer.

335 It is well known that the geothermal gradient is perturbed by infiltra-
 336 tion, and a number of investigators have used this effect to assess subsurface
 337 fluid flow as a function of measured temperature profiles. In the present case,
 338 however, the applicability of published models of coupled heat/fluid flow is
 339 questionable. The study area is located within a zone of groundwater dis-
 340 charge, as demonstrated by the large number of springs and seeps scattered
 341 about the meadow, so the potential gradient drives fluid flow upward every-
 342 where in the vicinity of the springs. Furthermore, the potentiometric surface
 343 is located within centimeters of the land surface. In the fine-grained silts
 344 that comprise the surficial sediments in the area, the capillary fringe would
 345 be expected to extend to the land surface; as a result, the soils are proba-
 346 bly saturated to the atmosphere-land interface, and there is little pore space
 347 available to accommodate infiltration. It is therefore likely that the main im-
 348 pact of precipitation on the shallow ground temperatures is due to contact
 349 cooling at the land surface, resulting in a modest depression of temperatures,
 350 distributed equally across the site. This accords with the observed changes
 351 in shallow ground temperatures, which can be explained by changes to other
 352 parameters at the boundary, as discussed below, without appeal to significant
 353 amounts of infiltration cooling.

354 To examine the effects of changing environmental conditions other than

infiltration at the land surface boundary, we used a simple 1-dimensional, steady-state model of conductive heat transfer. The model domain runs vertically from $z = 0$ at some arbitrary depth below the land surface to the land-atmosphere boundary at $z = L$. The field equation is given by:

$$\frac{d^2T}{dz^2} = 0, \quad (5)$$

subject to boundary conditions:

$$\frac{dT}{dz}(z = 0) = -\frac{q_z}{K_T}, \quad (6)$$

$$\frac{dT}{dz}(z = L) + \frac{h}{K_T} [T(z = L) - T_\infty] = 0, \quad (7)$$

where T is the temperature as a function of position, h is the coefficient of convective heat transfer [$\text{W}/\text{m}^2\text{C}$], K_T is the thermal conductivity of the porous medium [W/mC], q_z is a specified heat flux ($[\text{W}/\text{m}^2]$, positive in the vertical-upward direction), and T_∞ is the air temperature far from the land-atmosphere boundary. The boundary condition in Equation 7 is a Type III, or *conduction/convection boundary*, that balances the rate at which heat can be transmitted to the land surface through the porous medium by conduction with the rate at which heat can be carried away from the boundary by convection of the atmosphere. Equation 5 predicts a linear temperature gradient; by fitting the constants of integration to the boundary conditions we find the particular solution:

$$T(z) = \frac{q_z L}{K_T} \left(1 - \frac{z}{L}\right) + \frac{q_z}{h} + T_\infty. \quad (8)$$

The influence of changes in the various parameters on the measured temperatures can be examined using the relationship for model sensitivity, S , (Meyer, 2004):

$$S(\theta, \phi) = \frac{\phi_0}{\theta_0} \frac{d\theta}{d\phi} (\theta = \theta_0, \phi = \phi_0), \quad (9)$$

where θ is the dependent variable, ϕ is a parameter, and θ_0 and ϕ_0 are the initial values of θ and ϕ , respectively. Sensitivity is a normalized measure of how much one variable will change as the result of a small change in another variable or parameter. For example, if $S(\theta, \phi) = 2$, a 10% increase in ϕ will cause a 20% increase in θ . Similarly, for $S(\theta, \phi) = 0.5$, a 10% decrease in ϕ

will result in a 5% decrease in θ . For negative sensitivities, an increase in the parameter will result in a decrease of the dependent variable; otherwise, the ratios work the same way as for positive sensitivities. Equation 9 is known as the *sensitivity of θ to small changes in ϕ* (Meyer, 2004), and is usually used to determine the impact of a small estimation error in a parameter (in this example, ϕ) on the predicted value of the dependent variable (θ); here, we use it to determine the dependance of the observed shallow ground temperatures on the various parameters in Equation 8.

Since the length L in Equation 8 is arbitrary, the three parameters that may influence $T(z)$ are: T_∞ , K_T , and h . The most obvious influence on the observed ground temperatures is the change in air temperature between the Bravo and 2Bravo data sets; therefore, we first examine the sensitivity of observed temperature, $T(z)$, to a small change in the air temperature, T_∞ :

$$S[T(z), T_\infty] = \frac{T_{\infty,0}}{T_0(z)} \frac{dT(z)}{dT_\infty} (T_0(z), T_{\infty,0}), \quad (10)$$

$$= \frac{T_{\infty,0}}{T_0(z)} (1) = \frac{T_{\infty,0}}{T_0(z)}. \quad (11)$$

For an example, we can take parameter values from the Bravo data set. For air temperatures $T_{\infty,0}$ on the order of 20°C (Figure 8), and ground temperatures varying between $14.9 \leq T_0(z) \leq 33.5^\circ\text{C}$ (Table 1), sensitivities would fall in the range of approximately $1.3 \geq S(T(z), T_\infty) \geq 0.6$. In other words, cooler ground temperatures are slightly more sensitive to a decrease in the air temperature than warmer ground temperatures. For example, a 5.0°C (25%) decrease in T_∞ would result in a 4.8°C (32.5%) decrease in the observed ground temperature $T(z)$, while the same decrease in T_∞ would lead to a 5.0°C (15%) decrease at the highest temperature point. The overall effect is therefore to lower ground temperatures across the site more or less evenly, without decreasing the skewness or contributing to the observed compression of the range of temperatures.

Of the two remaining parameters, we would not expect K_T to vary as a function of changes in the weather (assuming no changes in water content of the soils). On the other hand, the convection coefficient, h , quantifies the ability of a fluid (in this case, the atmosphere) to carry heat away from the interface, and is generally a function of the thickness of the boundary layer, the surface geometry, the type and rate of fluid motion, and the thermodynamic properties of the convecting fluid (Incropera and DeWitt, 1990). These factors can all change with changing environmental conditions, influencing heat transfer at the upper model boundary. Calculating the sensitivity

413 of $T(z)$ to small changes in the coefficient of convective cooling yields:

$$S[T(z), h] = \frac{h_0}{T_0(z)} \frac{dT(z)}{dh} (T_0(z), h_0), \quad (12)$$

$$= -\frac{h_0}{T_0(z)} \frac{q_z}{h^2} (T_0(z), h_0), \quad (13)$$

$$= -\frac{1}{T_0(z)} \frac{q_z}{h_0}. \quad (14)$$

414 Equation 14 shows that the sensitivity of the observed temperature to a
 415 change in the coefficient of convective cooling, h , is not solely a function of h ,
 416 but also of the magnitude of the heat flux, q_z . However, the heat flux is not
 417 independent of the temperature $T(z)$, since Equation 8 can be rearranged
 418 to give an expression for heat flux as a function of z :

$$q_z = \frac{[T(z) - T_\infty] K_T h}{L - z + K_T}. \quad (15)$$

419 If we associate L with the depth of the shallow temperature measurements
 420 (in this case, 0.2 m), then $z = 0$ and Equation 15 reduces to:

$$q_z = \frac{[T(z=0) - T_\infty] K_T h}{L + K_T}. \quad (16)$$

421 We can make the above simplification without loss of generality, because
 422 the linear gradient implicit in Equations 5 implies a constant flux for all
 423 depths. Substituting Equation 16 for q_z in Equation 14 yields an expression
 424 for the sensitivity of temperature $T(z)$ to a small change in the coefficient of
 425 convective heat transfer h :

$$S[T(z), h] = \frac{K_T [T_0(z) - T_\infty]}{T_0(z) (L + K_T)}. \quad (17)$$

426 For comparison with the sensitivities to far-field air temperature changes,
 427 we can take parameter values from the Bravo data set, letting $L = 0.2$ m
 428 and $T_\infty = 20^\circ\text{C}$. Assuming a thermal conductivity $K_T = 0.665$ W/m $^\circ\text{C}$,
 429 and taking the minimum and maximum shallow ground temperatures from
 430 the Bravo data, $T_0(z=0) = 14.9$ and $T_0(z=0) = 33.5^\circ\text{C}$, we find the
 431 sensitivities range from 0.263 to -0.310, respectively. Thus, for an initial
 432 value of $h_0 = 20$ W/m $^2^\circ\text{C}$, a 10 W/m $^2^\circ\text{C}$ increase in h (50%) would result
 433 in an *increase* of $\approx 2.0^\circ\text{C}$ in the lowest temperature area, while the same
 434 10 W/m $^2^\circ\text{C}$ increase in h would result in a *decrease* of around 5.2°C in the

435 highest temperatures. The zero-sensitivity point is $T_0(z = 0) = T_\infty$; all tem-
 436 peratures $T_0(z = 0) < T_\infty$ will increase for increasing h , while all tempera-
 437 tures $T_0(z = 0) > T_\infty$ will decrease for increasing h . Changing h therefore
 438 impacts the highest/lowest temperature (or flux) areas most strongly, reduc-
 439 ing the distribution skewness and compressing the range of shallow ground
 440 temperatures, moving all temperatures closer to T_∞ .

441 Of course, heat transfer at the site is far more complex than portrayed by
 442 the model described here. The simple 1-dimensional model results are pre-
 443 sented to demonstrate the general effects and relative importance of changes
 444 in the various heat transfer parameters perturbed by environmental condi-
 445 tions. A more complete model of the impacts of enviromental change on
 446 shallow ground temperatures would incorporate transient behavior, as well
 447 as other heat transfer modes such as radiation and evaporation, and would
 448 require accurate measurements of precipitation rates and temperature, evap-
 449 otranspiration, near-surface soil permeability, water content, etc. Most of the
 450 required quantities are poorly constrained or unavailable for our site; how-
 451 ever, we contend that “precise” modeling of the shallow temperature varia-
 452 tion is less important than an understanding of the general behavior of the
 453 system.

454 4.2. Geostatistical Analysis

455 In contrast to the depression of temperatures noted in the direct temper-
 456 ature comparison, the inferred spatial correlation function showed only minor
 457 influence from the change in atmospheric conditions. Neither set of residuals
 458 from the cross-validation exercises demonstrated correlation, and both sets
 459 of residuals showed a mean not significantly different from zero at the 95%
 460 confidence level (i.e., 0.05 significance). Although the central portions of the
 461 QQ plots conform well to the theoretical/sample distribution line, both sets
 462 of residuals showed heavier tails than would typically be expected from a
 463 Gaussian (normal) distribution (Figure 7, b and d). Because it is essentially
 464 a low-pass filter, the kriging interpolator tends to overestimate low values and
 465 underestimate high values of an estimated variable. As a result, it is common
 466 for cross-validation residuals to demonstrate poor performance when estimat-
 467 ing extreme values. The change in the tails of the distribution of residuals,
 468 as shown in Figure 7 b and d, indicate the 2Bravo spatial correlation model
 469 does a somewhat poorer job of predicting the extreme values of temperature
 470 when applied to the Bravo data. In spite of this change, the residuals for the
 471 Bravo cross-validation actually show a slightly smaller standard deviation

472 (0.054 vs. 0.060°C), as well as a smaller mean squared prediction error (1.33
473 vs. 1.46°C), in comparison to the cross-validation residuals for the 2Bravo
474 dataset (see Table 1).

475 On the basis of the testing of the cross-validation residuals, it appears
476 that the spatial correlation of the measured temperatures of the Bravo and
477 2Bravo data sets is reasonably well described by the same model variogram.
478 However, variograms generally give information about the scale of variability
479 of a spatially-correlated random function, but not about the actual values;
480 thus, two realizations of the same generating process may look very differ-
481 ent, but still share the same model variogram. Furthermore, variograms often
482 mask patterns in a data set that would be clear from another type of plot
483 (Kitanidis, 1997). It is therefore worthwhile to ask what can be learned
484 from the variogram, and whether the apparent robustness of the variogram
485 may be useful in situations where the actual patterns of shallow temperature
486 distributions are obscured by environmental perturbations.

487 In spatial statistics the observed data are commonly referred to as a “re-
488 alization” (corresponding to a “sample” in classical statistical theory), which
489 is assumed to arise from an underlying and usually unknowable “generating
490 process” (analogous to the “population” of classical statistics). In common
491 with all types of statistical inference, the goal of analysis is to identify the
492 properties of the underlying generating process on the basis of (limited and
493 incomplete) observed data (Deutsch and Journel, 1998). The characteris-
494 tics and parameterization of the model variogram that represents a particular
495 field situation therefore provide information about the underlying process(es)
496 that give rise to the field observations. For example, choosing a Gaussian
497 model variogram over a spherical or exponential model to represent a data
498 set implies that the data vary smoothly at short spatial scales, because Gaus-
499 sian model variograms are differentiable at the origin(Kitanidis, 1997). In
500 addition, Gaussian models have a finite range with a well-defined sill. This
501 is in contrast to spherical models, which have spatial correlation over a finite
502 length scale but are nondifferentiable at the origin, or exponential models
503 which are nondifferentiable at the origin but demonstrate spatial correlation
504 that only goes asymptotically to zero as the separation vector goes to infin-
505 ity. Similarly, linear or power models represent nonstationary variability, and
506 are often associated with fractal processes, while hole effect models represent
507 pseudo-periodic behavior (Kitanidis, 1997). Representations of data variabil-
508 ity using indicator variograms may also provide information on subsurface
509 processes by identifying regions resulting from different generating processes;

for example, to differentiate between areas of fractured and unfractured rock (Pollyea et al., 2013). Other characteristics and parameters of model variograms that may offer insight regarding the underlying generating processes include the amount, type, and orientation of anisotropy, the size (and orientation, for anisotropic systems) of any “nugget effect,” and the range of the variogram (or lack of a well-defined sill, for non-stationary processes).

Of course, there is no unique “true” model variogram for the Bravo/2Bravo data (or for any other data set; see Kitanidis (1997)). It is possible that another model variogram could fit the data as well, or even better, in the sense of having a smaller mean squared prediction error, than the model proposed in Table 2. However, from the analysis given here, it appears likely that any model that fits one data set will also provide an adequate description of the spatial correlation structure of the other and, by extension, that inferences drawn about the underlying generating process(es) on the basis of a “perturbed” data set will also apply to an “unperturbed” data set.

There are several additional aspects of the present study that deserve particular attention. First of all, it is important to note that we chose the 2Bravo dataset, which was taken after temperatures in the study area had been impacted by changing conditions, as a conditioning data set for model development. A common situation faced by investigators is the need to collect data under nonideal conditions (for example, during or soon after rainfall or changing weather, or on consecutive days with different air temperatures), particularly when working in mountainous or remote field areas. A data collection procedure that requires an investigator to stop work and wait for ideal conditions is costly and often impractical. The results presented here indicate that the usefulness of shallow temperature data for directly visualizing subsurface processes (e.g., Fairley and Hinds, 2004a) may be adversely impacted by nonideal conditions; however, studies for which the objective is to identify the spatial correlation structure of the underlying generating processes (e.g., Anderson and Fairley, 2008) should be minimally impacted.

A second point worthy of discussion is the sources and magnitudes of the different factors that contributed to the ground temperature perturbation in the present study. The observed changes in the shallow temperature distribution result from a complex mix of factors; however, the analysis of Section 4.1 shows that the general trends can probably be accounted for by a combination of decreasing air temperature and increasing convective heat transfer. The exact amount of precipitation at the study site is not well con-

strained but, as discussed earlier, the role of direct heating of infiltration in the overall lowering of ground temperature is likely to be relatively minor. On the other hand, any precipitation that became runoff or remained in puddle storage would contribute to an increase in the apparent convective heat transfer coefficient and subsequent decrease in skewness and range compression of the shallow temperature field. Other factors may also have influenced the convective heat transfer coefficient, such as an increase in wind speed and increasing relative humidity of the atmosphere. Given the large number of factors that may impact shallow ground temperatures, it is unlikely that any measured shallow ground temperature field could be considered “unperturbed.” Thus, our objective for this study has been to show that shallow temperature observations can generally be relied upon for making inferences about the spatial correlation structure (i.e., the model variogram) of the temperature field, even when the data are acquired under nonideal conditions.

It should be pointed out that conductive heat flux within the Bravo grid probably averages around 10 W/m^2 , which is quite high. In their investigations of ground temperatures and heat flow in the Basin and Range province of Nevada, Olmsted and Ingebritsen (1986) found that mean annual near-surface temperatures (measured at 1 m depths) were highly correlated with heat fluxes measured in boreholes for heat flows of greater than about 0.2 W/m^2 . For fluxes less than this amount, the investigators found that mean annual temperatures were more strongly correlated with albedo, whereas heat flow was only weakly correlated with mean annual temperature. This suggests that 20 cm depth ground temperature surveys are best suited to high flux environments such as the Bravo grid, the hydrothermal discharge areas of southeast Oregon (Fairley and Hinds, 2004a), the hydrothermal fields of New Zealand investigated by Rissmann et al. (2011), etc. In these types of high flux environments, the goal is usually to identify structural controls on hydrothermal discharge (Anderson and Fairley, 2008; Rissmann et al., 2011), to delineate areas of high permeability and/or fracturing (Fairley and Hinds, 2004b; Heffner and Fairley, 2006), or define near-surface fluid circulation patterns (Fairley and Hinds, 2004a). Although the shallow heat flux in these systems is likely to exceed the 0.2 W/m^2 threshold identified by Olmsted and Ingebritsen (1986), those investigators did not record precipitation during their fieldwork, and were working with annual average temperatures. It is therefore encouraging to note from the present analysis that observed spatial correlation structure of shallow temperatures will be minimally impacted by

586 precipitation and changing air temperatures.

587 5. Conclusions

588 We measured shallow ground temperatures in the vicinity of a small group
589 of hot springs in Yellowstone National Park, Wyoming. The measurements
590 were made at a depth of 20 cm, over a 72×72 m area, at a resolution of
591 3×3 m. The initial survey was made during a period of dry weather; a
592 second survey was made three days later, following a series of light to mod-
593 erate precipitation events and cooling air temperatures. Basic statistics and
594 point-by-point differencing of the two temperature fields showed a decrease
595 in skewness and range, and overall depression of ground temperatures during
596 the second survey in comparison to the first survey; however, the spatial
597 correlation structure of the two data sets demonstrated little influence of
598 changing atmospheric conditions on the surface expression of the underlying
599 generating function.

600 The results of the Bravo/2Bravo analysis have important implications
601 for the use of temperature as an indicator of shallow subsurface processes.
602 Although the measurement of ground temperatures at 1 m depths is a com-
603 mon approach to evaluating near-surface ground temperatures, it is time
604 consuming and labor intensive, necessarily limiting the number (and hence
605 the spatial density) of observations that can be made. In contrast, mea-
606 suring temperatures at shallow (≤ 25 cm) depths allows rapid collection of
607 large, spatially-referenced data sets for geostatistical analysis or the imaging
608 of near-surface heat and fluid flow (e.g., Fairley and Hinds, 2004a,b; Fairley
609 and Nicholson, 2006; Anderson and Fairley, 2008).

610 Although the investigation presented here was conducted in a magmatically-
611 heated hydrothermal system, we expect the findings to hold in any high heat
612 flux environment. It is less clear to what extent the conclusions drawn here
613 may apply to lower flux environments but, on the basis of the findings of
614 previous investigators (e.g., Olmsted and Ingebritsen, 1986), we expect our
615 conclusions to hold for most systems exhibiting a near-surface heat flux some-
616 what greater than 0.2 W/m². The study findings therefore suggest that site
617 evaluation using high-resolution, spatially-referenced shallow ground tem-
618 perature measurements is a robust method for identifying spatial correlation
619 structure in high flux environments.

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