The Use of Wavelet Analysis to Derive Infiltration Rates from Time-Lapse One-Dimensional Resistivity Records

As part of a study to understand factors impacting the efficiency of an artificial recharge pond in Watsonville, CA, a time series of resistivity measurements was made using a permanently installed one-dimensional resistivity probe. Measurements were made in the top 2 m of sediment with data acquired every 30 min. There was an observed diurnal signal in these data due to daily temperature fluctuations in the pond water. By viewing this signal as a thermal tracer, we used the movement of the associated thermal front to estimate infiltration rates from the resistivity data. We developed a wavelet-based method for calculating lag times of the thermal front between measurement locations. As part of this algorithm, we tested the statistical significance of a given signal and automatically rejected calculated lag times that were associated with signals below a given confidence interval. We included a linear inversion routine for calculating the velocity of the thermal front from the calculated lag times. Using the thermal velocity, we estimated an infiltration rate at the resistivity probe that decreased from approximately 3.5 to 1 m $d^{-1}$ during a period of 18 d. Resistivity data have a distinct advantage over direct temperature measurements: a resistivity measurement is sensitive to changes outside the region disturbed by instrument emplacement. While our processing approach was demonstrated on the presented resistivity data, it is equally valid for use with direct temperature measurements.

Abbreviations: CWT, continuous wavelet transform; XWT, cross-wavelet transform.

A growing component of water resource management is the development of systems for the subsurface storage and subsequent recovery of water. At many locations throughout the western United States, this is accomplished through the use of recharge ponds. A recharge pond is filled with water during the months when there is available surface water; the pond water percolates into the subsurface, and the water is then recovered at other times of the year to supplement the supply of surface or groundwater. Central to the successful operation of such a system is the need for information about the subsurface processes and properties that govern the quantity and quality of stored and recovered water. In the southwestern United States, there are several recharge ponds that have been the focus of long-term studies (e.g., Izbicki et al., 2007, 2008).

One critical process in the use of a recharge pond is the infiltration of the pond water into the subsurface. In the operation of most ponds, there is a limited period of time (e.g., the rainy season) when the pond can be filled with water and the subsurface storage region recharged. During that time period, the challenge is to ensure that sufficient pond water infiltrates so as to maximize subsurface storage; this requires maintaining an optimal infiltration rate. In this study, we worked at the Harkins Slough recharge pond, located approximately 5 km west of Watsonville, CA, and 1 km from the coast. The infiltration rate in the pond has been found to decay rapidly with time, thus significantly limiting the amount of stored water. The cause of this decay has been presumed to be clogging of the pore space through which the water percolates due to the accumulation of fines or the buildup of biomass associated with microbial activity.

The method currently used to determine the infiltration rate at the base of the pond is a simple mass balance, where the pumping rates for adding water to the pond and the measured changes in the height and areal extent of the pond are used to provide a pond-scale average (Racz et al., 2008). As such, this measure of infiltration contains no detailed information about the spatial and temporal variability in the infiltration rate across the pond....
We focused on isolating the component of the resistivity data that
 Temperature fluctuations obtained from point measurements
 Hatch 2008) or time-series analysis (e.g., Hatch et al., 2006; Keery et al.,
 In this study, we: (i) acquired evidence of a measurable diurnal
direct-temperature sensors are point measurements and as
 Our field experiment allowed us to assess the use of vertical profiles
 Electrical resistivity measurements are well suited for this appli-
 The near-surface geologic material underlying the pond is predominantly well-sorted, medium- to coarse-grained sand. The
 changes in electrical resistivity in the region below the pond are therefore determined by changes
 We focused on isolating the component of the resistivity data that captured the change in temperature of the infiltrating pond water,
 When making measurements using an emplaced subsurface measurement device (such as a probe), there is a key advantage to using resistivity measurements,
 The direct-temperature sensors are point measurements and as such can be significantly affected by the disturbed zone immediately adjacent to the device. Electrical resistivity measurements are not point measurements but volume averages that are sensitive to the properties away from the measurement device.
 Temperature fluctuations obtained from point measurements have been used to infer infiltration rates through either numerical modeling (e.g., Constantz and Stonestrom, 2003; Constantz, 2008) or time-series analysis (e.g., Hatch et al., 2006; Keery et al., 2007). In this work, we built on the time-series approach of Hatch et al. (2006), which had previously demonstrated the use of signal analysis of temperature records for determining infiltration rates. In their work, diurnal temperature fluctuations acted as a periodic temperature forcing, and streambed infiltration rates were estimated from time-series analysis of vertical temperature profiles. Our field experiment allowed us to assess the use of vertical profiles of electrical resistivity measurements as an alternative or complementary means of monitoring and quantifying infiltration rates.

In this study, we: (i) acquired evidence of a measurable diurnal temperature signal in resistivity records, (ii) developed a wavelet-based method for calculating lag times of the associated thermal front between measurement locations, and (iii) developed a linear inversion routine for calculating the velocities of the thermal front based on the calculated lag times. Finally, we applied the approach of Hatch et al. (2006) to convert these thermal velocities to infiltration rates. While our processing approach is demonstrated on the presented resistivity data, it is equally valid for use with direct temperature measurements and can be applied to either data set without modification of the approach.

Site

The Harkins Slough recharge pond, which has been in operation since the fall of 2001, was designed and constructed by CH2M Hill and is owned and operated by the Pajaro Valley Water Management Agency (PVWMA, Watsonville, CA). The oval-shaped pond, depicted in Fig. 1, is approximately 300 by 100 m. It has a shallow outer bench, approximately 1.5 m deep, and when full reaches a water depth of 5 m at the deepest point. During winter storms, overland flows drain into Harkins Slough, which is surrounded by agricultural fields. A small portion of the flow through the slough (a maximum of approximately 2.5 × 10⁶ m³ or 2000 acre-feet each winter between 1 November and 31 May) is diverted and pumped into the recharge pond. The pond is filled with water during the winter months (typically January–May); the water percolates through the base of the pond and is stored in the underlying aquifers. Water is retrieved from recovery wells around the pond throughout the year to supplement the delivered water supply and reduce the groundwater needs of the local farmers in this coastal zone. The pond, when full, can hold approximately 5.4 × 10⁸ m³ (44 acre-feet) of water and has had recorded volumetric infiltration rates exceeding 2.47 × 10³ m³ d⁻¹ (20 acre-feet d⁻¹). Due to the decrease in infiltration rate, however, the PVWMA was only able to infiltrate approximately 1 × 10⁶ m³ (~800 acre-feet) during the 2008 operation year (January–May.)

Electrical Resistivity Measurements

To monitor the infiltration processes at the pond, we developed an inexpensive one-dimensional resistivity probe designed for measuring changes in the subsurface electrical resistivity. The probe, made of a 3-m polyvinyl chloride pipe, was equipped with

---

**Fig. 1.** Map view schematic of the Harkins Slough recharge pond, showing approximate locations of the water inlet and resistivity probe. The dashed contour represents the approximate boundary between the shallow outer bench and the deeper inner section. The outer solid boundary denotes the edge of the pond.
35 stainless steel electrodes, evenly spaced at 8.5-cm intervals. The probe was installed near the center of the pond in December 2007, with the top meter left above the ground to provide a measure of the electrical resistivity of the pond water. The probe was connected to an autonomous monitoring system, with data being acquired every 30 min for the duration of pond operation from January to March 2008.

Electrical resistivity measurements involve injecting current $I$ through one pair of electrodes and measuring the drop in potential, $\Delta V$, between another pair of electrodes. Measurements were made using a standard four-electrode Wenner array; for 35 electrodes, this yields 32 unique measurements of resistance $R$, where $R = \Delta V/I$. When the current is injected, the surrounding three-dimensional resistivity structure determines the potential that will be measured at all locations for a given input current. To obtain true resistivity values, these measurements need to be inverted; however, the apparent resistivity can easily be calculated which provides an estimate of the in situ resistivity. The apparent resistivity, $\rho_{\text{app}}$, is calculated as

$$\rho_{\text{app}} = K \frac{\Delta V}{I}$$  \hspace{1cm} [1]$$

where $K$ is a geometric factor specific to each measurement location. The calculation of $K$ is trivial, requiring only electrode locations and the location of the free surface (see, for example, Telford et al., 1990). With an apparent resistivity calculated at each depth, we produced a depth–time plot of electrical resistivity below the pond (Fig. 2).

Figure 2 shows the apparent resistivity record from the probe. Depth equal to 0 corresponds to the bottom of the pond, with positive depth values indicating increasing depth. The main feature in the figure is the significant change in the measured apparent resistivity at 300 h in the pond water (shown at depths <0 m) and moving into the subsurface (shown at depths >0 m) several hours later. Within the first 300 h of pond operation, the apparent resistivity of the pond water was at its lowest values, i.e., the pond water was the most conductive. This is to be expected because this was water from the first major storm of the year, which washed residual fertilizers and salts, as well as fine-grained sediments, from local agriculture fields and hence had a higher fraction of dissolved and suspended solids than water arriving later in the winter. In fact, pumping was stopped between approximately 200 and 300 h because the water was too turbid to be suitable for infiltration. Corresponding to the time that pumping was resumed at approximately 300 h, a large increase in fluid apparent resistivity was evident; as the rains continued, the ground surface within the watershed became progressively cleaner. This change in apparent resistivity can be tracked into the subsurface data in Fig. 2.

The changes in apparent resistivity in the pond water can be seen in more detail, as is done in Fig. 3a, in a plot of the apparent resistivity signal at one measurement location in the water column (from a depth of −0.5 m in Fig. 1). In addition, a temperature time series is presented in Fig. 3b of the temperature of the pond water obtained using a HOBO TidbiT temperature sensor (Onset Computer Corp., Bourne, MA) also located 0.5 m above the pond bottom. The large-scale variations in the apparent resistivity of the pond water, seen in Fig. 2, is also seen in Fig. 3a. There was initially a decrease in apparent resistivity in the first few hours as the water, containing relatively high amounts of dissolved and suspended solids, entered the pond; resistivity then stayed relatively constant until the jump in the fluid apparent resistivity, clearly seen just after 300 h, when the pump was restarted. There was a decrease in the temperature of the pond at this point, suggesting that the change in apparent resistivity was due to a combination of temperature and salinity effects and probably reflects the influx of fresher, colder water.

![Fig. 2. Time series of one-dimensional apparent resistivity data; 0 on the depth axis indicates the pond bottom (indicated by the dashed line), while negative values indicate the height above the pond bottom.](image)

![Fig. 3. (a) A single apparent resistivity time series from a depth of −0.5 m (i.e., middle of the water column); (b) a temperature time series from a depth of approximately −0.5 m.](image)
Between 400 and 600 h, there was a gradual increase in apparent resistivity. Because temperature was relatively constant during this time period, we concluded that the dominant factor controlling the general trend in apparent resistivity during this time period was the decreasing salinity of the pond water; i.e., the pond water was becoming progressively cleaner. Around 650 h, the trend reversed and there was a gradual decrease in apparent resistivity. As can be seen in Fig. 3b, this corresponds to a trend in increasing water temperature in the pond. This increase in temperature was due to atmospheric forcing as a warm front moved into the region. Using an estimate of a 2% change in fluid resistivity per degree Celsius (Brassington, 1998), we would expect to see a decrease in electrical resistivity of approximately 6% for the time window between 650 and 800 h (assuming constant fluid salinity). This estimate corresponds well with the observed decrease (Fig. 3a) of approximately 7%. We suggest that in this time window, when pumping rates were constant and there was no precipitation, long-time-scale (>2-h) temperature changes were the dominant drivers of the apparent resistivity changes.

What are of interest in Fig. 3b are the diurnal temperature fluctuations throughout the entire record. When the resistivity data shown in Fig. 3a are considered, this diurnal signal is seen between 650 and 950 h, captured as fluctuations in the magnitude of the apparent resistivity. We note that while the diurnal signal is particularly clear during this interval, it is present at some earlier times in the image. At these earlier times, the fluctuations at lower resistivity values are masked in the plot by the large overall range of resistivity values.

Our review of the resistivity data led us to conclude that there were two variables, the salinity and temperature of the pond water, that caused the observed changes in the electrical resistivity at both large and small temporal scales. The change in the salinity and the change in mean daily temperature of the pond water both resulted in changes in resistivity at temporal scales on the order of 10s to 100s of hours. The diurnal temperature fluctuation resulted in changes in resistivity at a smaller temporal scale, on the order of ∼24 h.

**Processing: Isolating the Diurnal Resistivity Signal**

Motivated by prior work focused on using temperature signals to infer infiltration rates through time-series analysis (e.g., Hatch et al., 2006; Keery et al., 2007), we developed an approach for capturing, and using, the diurnal signal in the resistivity data to quantify infiltration rates. By measuring the lag times of the associated thermal front as a function of depth, we can estimate the infiltration rate at the probe location. Figure 4 schematically depicts this. As the alternating warm and cold phases propagate in the subsurface, this signal is measured using absolute temperature or electrical resistivity. As seen in the image, a given thermal front (due to diurnal heating or cooling) will arrive at a near-surface sensor earlier in time than at a deeper measurement location. By calculating the lag time between these two locations, we can obtain the velocity of the thermal front.

Both resistivity and temperature records are nonstationary. Recent work by Henderson et al. (2009) demonstrated the use of wavelets for analysis of temperature data from distributed temperature sensors. In addition to the work of Henderson et al. (2009), wavelets have been used in the hydrologic sciences by Labat (2008, 2010) for analyzing large-scale freshwater stream discharge. These works highlight the fact that wavelet processing is useful when signals are nonstationary and the frequency content of a signal needs to be localized as a function of time. We therefore adopted wavelet processing as the method for determining the velocities of the thermal front.

**Wavelets**

The initial part of our workflow involves using wavelet analysis to identify regions of measurable and reliable diurnal signals. An image is then constructed of the thermal front lag time as a function of depth and time. That is, images are produced that display the time it took, relative to some reference point, for the thermal front to move from a defined reference depth.

Wavelet analysis is well suited for dealing with nonstationary signals such as those often encountered in geophysical data (such as the resistivity data from the pond). Wavelets are signals that are localized in both time and frequency; as such, they provide an excellent tool for characterizing the frequency content of a signal as a function of time. The use of, and theory behind, wavelets was well described by Kumar and Foufoula-Georgiou (1997) and Torrence and Compo (1998). In this study, we used the continuous wavelet transform (CWT) and the cross-wavelet transform (XWT). The CWT convolves a wavelet with a time-domain signal, as described by

\[
W^X_n (s) = \sqrt{\int_{t} \sum_{n=1}^{N} x_n^2} \psi_0 \left( n' - n \right) \frac{\delta t}{s}
\]  

(2)

![Fig. 4. A schematic of the thermal front propagating into the base of the pond. Red bars indicate warmer water while blue indicates cooler water. At a given measurement location, there is a decrease or increase in the resistivity corresponding to the warmer and cooler water, respectively. The measured signals at two different depths, as depicted by the dashed and solid lines, can be used to calculate the time it takes the thermal front to propagate between the measurement locations; Δφ is the phase lag.](Image 342x154 to 536x273)
where $W'_nX(s)$ is the transformed time series for a given scale $s$ (e.g., in our case the period $[h]$ of the signal), $x_n$ is the time series, $\delta t$ is the time step, $n$ is the time, and $n'$ is reversed time (Grinsted et al., 2004). The function $\psi_0$ is the wavelet function under consideration. There are several candidate wavelet functions (Torrence and Compo, 1998). For this work, we chose to use the Morlet wavelet; it is a complex function, so both amplitude and phase information can be obtained from its use. A power spectrum is produced from Eq. [2] by taking $|W'_nX(s)|^2$ and normalizing by the signal variance. This can be thought of as equivalent to a Fourier power spectrum; with wavelets, however, there is no assumption of a periodic signal.

Figure 5a presents a CWT of the resistivity signal in the sediment underlying the pond at a depth of $\sim 0.17$ m. We note that with each depth there is an associated time series and therefore a CWT. Shown on the figure is a dashed line corresponding to a period of $24 \text{ h}$, the signal component of specific interest in this study. When calculating the CWT there is no padding of the temporal signal so that there are edge effects at the beginning and end of each signal. The faded regions on the left and right of the image indicate zones with edge effects in the CWT; the CWT is unreliable in this region. Also shown are the 95% CIs (bold black lines). These CIs are the results of a statistical significance test of the wavelet spectra conducted using the method described in Torrence and Compo (1998). The CIs indicate that the signal contained within the contours has a 95% likelihood of being significant when compared with a CWT of a red-noise spectrum. Red noise tends to have characteristics similar to many geophysical signals because it has low-frequency noise with a larger amplitude than high-frequency noise (Torrence and Compo, 1998).

There are several key features to note in the CWT in Fig. 5a. First, at approximately 300 h, there is a high-amplitude, wide-spectrum signal that swamped any diurnal fluctuations. This signal is coincident with the rapid jump in apparent resistivity at approximately 300 h. Between approximately 500 and 950 h, there is substantial energy that is isolated around the 24-h period. This energy is of lower magnitude than the signal at $\sim 300$ h, but it was still judged to be statistically significant falling, as it does, within the 95% confidence internals.

Figure 5b is the CWT from within the sediments at a depth of 0.68 m. It is clear that the isolated diurnal signal decayed in late time (i.e., $>850$ h) and was only above the 95% CI between 500 and 850 h. This was to be expected; the heat was dissipating with depth, so the measurable effect on resistivity was reduced. By inspecting Fig. 5, we were able to use the CWTs to determine which regions in our time series contained a significant 24-h signal.

To generate an image of lag time as a function of depth and time, we needed to relate the signal from a given reference depth to the signals at all other depths of interest. This was done using the XWT to determine the regions of the two CWTs with high coincident power. The XWT is calculated as

$$W^{XY} = W^XW^Y*$$

where $W^{XY}$ is the cross wavelet transform, $W^X$ is the real component of the CWT for a reference time series (i.e., the time series at a given depth), and $W^Y*$ is the complex conjugate of the CWT for another time series (i.e., in our case, the time series at some other depth). The power spectrum is defined as $|W^{XY}|^2$. A phase spectrum can be obtained by taking the phase angle between the real and complex portions of the XWT. We used the phase spectrum to calculate the lag times for a given depth interval as a function of time.

Figure 6 is the XWT for the signals from Fig. 5 at depths of 0.17 and 0.68 m. There is substantial energy, centered about the 24-h
negative lag: Our reference depth was selected to be at 0.17 m. The following are the three criteria that we used for accepting or rejecting a calculated lag time:

1. Broadband signal: If the dominant signal (at a given time) was not isolated around the 24-h period, we did not calculate a lag time. While there might have been a signal in the 24-h period, if it was not isolated we could not guarantee that it was due to the diurnal temperature fluctuations.

2. Negative lag: Our reference depth was selected to be at 0.17 m below the pond bottom. Invoking the argument of causality, if we calculated a negative lag time, indicating that the reference signal trailed the other signal, we rejected the data. We expected our thermal front to have propagated downward; therefore, a negative lag time was impossible and was taken to indicate low signal quality at a given depth and time.

3. XWT confidence interval: The XWT can have significant energy in a region where only one of the corresponding CWTs has significant energy. To overcome this issue, we rejected phase lags that were calculated at periods or times that (i) did not satisfy the significance criteria as determined from the XWT spectrum, or (ii) did not satisfy the significance criterion for either of the individual CWT spectra.

Adhering to the above rules, we processed our filtered resistivity data to produce an image of lag time (Fig. 7). This figure spans the time window from 500 to 900 h, the region that was deemed to have a significant 24-h signal; regions of white had no discernible signal. Upon qualitative inspection of the figure, two points are clear: (i) the lag times get larger to the right, indicating that the infiltration rate is decreasing with time, and (ii) at later times, where the lag times are longer, the signal quality decays (due to heat loss), and hence the vertical extent of a measurable signal is much less.

Of the approximately 1000-h (~6-wk) record presented in Fig. 2, we were able to calculate lag times for approximately 40% of the recording period. The major factor that seems to have influenced our ability to use the diurnal signal in early time is that the pumping rates, and related pond height, varied during the first 500 h of operation. We surmised that this caused mixing in the pond that reduced the thermal signal. In particular, the rapid change in pond height occurred at approximately 300 h, which is coincident with the broadband signal in Fig. 6.

**Inverting for Thermal Velocity from Lag Time**

Processing the resistivity data using the wavelet analysis described above yielded a record of lag time, as shown in Fig. 7, as a function of measurement depth and time. We used these lag times to estimate the vertical velocity of the thermal front, referred to as the **thermal velocity**. Our approach involved formulating a linear inverse problem that allowed us to solve for thermal velocity as...
a function of time. We parameterized the forward model with a single thermal velocity at each time for all depths. Obviously, a multilayer model could be chosen where the thermal velocity varies with depth. We found, however, that with a single-layer model, we achieved a good data fit. Given that this simple model fit the data well, we felt there was no reason to introduce more model complexity. A more complex model can always fit the data, given the increase in degrees of freedom.

To invert the lag-time data, we first formulated a forward model at each time step. This model allowed us, for a given thermal velocity, to estimate the lag time at a given measurement depth:

\[
\begin{bmatrix}
    t_{n,i} \\
    t_{n+1,i} \\
    \vdots \\
    t_{m,i}
\end{bmatrix} = \begin{bmatrix}
    l_{n,i} \\
    l_{n+1,i} \\
    \vdots \\
    l_{m,i}
\end{bmatrix} \begin{bmatrix}
    s_{i}
\end{bmatrix} S_T^{-1} T
\]

where \(i\) is the time index, and \(n\) and \(m\) are depth indices, \(t_{n,i}\) is the lag time between the signal at the reference depth and the signal at the depth of interest for a given time in the record, \(l_{n,i}\) is the distance between the reference depth and the depth of interest, and \(s_{i}\) is the apparent thermal slowness, where \(\text{thermal slowness}\) is defined as the inverse of thermal velocity. Thermal slowness is used to keep the inverse problem in Eq. [5] linear. Using Eq. [5], we solved for lag time as a function of thermal slowness. Using a standard least-squares formulation, thermal slowness was determined, given a series of lag times, as

\[
S_T = (L^T W^T W L)^{-1} L^T W^T W T
\]

where \(W\) is a diagonal matrix that contains the inverse of the standard deviation of the lag times. We defined the covariance matrix for \(S_T\) as (Tarantola, 1987)

\[
C_S \sim (L^T W^T W L)^{-1}
\]

From this, we obtained the standard deviation of \(S_T\):

\[
\text{SD}(S_T) = \sqrt{\text{diag}(C_S)}
\]

We solved both Eq. [6] and [8] for each time step in the lag-time data set, thus generating a record of thermal slowness and an error estimate as a function of time. Thermal slowness was then easily converted to thermal velocity (\(V_T\)) by taking the reciprocal, where \(V_T = 1/S_T\).

### Results and Conclusions

Figure 8 presents the results of our inversion and infiltration velocity calculation. In Fig. 8a, we have the calculated infiltration rate at the probe along with error estimates obtained using Eq. [8]. In Fig. 8b, we have the estimated standard deviation of our data normalized by the measured lag time. For this analysis, we assumed that the lag times had a standard deviation of half of a sampling interval (e.g., 15 min), so that 95% of our measured lag times fell within ±1 standard deviation. We note that this model is optimistic in terms of true data errors because it only addresses the issue of temporal sampling. As can be seen in Fig. 8b, we had significantly higher relative error in the near surface; incorporating this information into our inversion allowed us to fit the deeper, more precise data to a higher tolerance. Figure 8c shows the error between the predicted lag times, given the velocity model in Fig. 8a, and the true lag times, presented as a percentage of true lag times. As with Fig. 8b, we see higher error toward the top of the model, with lower error toward the bottom. We note that Fig. 8c is not expected to be a perfect reproduction of Fig. 8b. This is because the predicted data used in Fig. 8c represent the best fit model, whereas the error model in Fig. 8b represents that error for a model that is biased by one standard deviation.

In Fig. 9, we present the results of our analysis, the estimated values of the infiltration rate, and the average infiltration rate calculated for the entire pond during the same time window. The estimated infiltration rate at our probe location was significantly higher than the average rate for the pond. It is not surprising to find spatial variability in infiltration rates across the base of the pond. Given that our probe was located at the lowest point in the pond, which would have a larger hydraulic gradient than other locations, we would expect to see a higher infiltration rate. What is more interesting is
the fact that infiltration at the probe steadily decreased with time, while the average rate actually increased during this time period. We attribute this to a change in the area covered by the pond at approximately 600 h. At this time, the pond reached the height where it began to flood the outer flanks of the pond. This new area had not yet been subjected to clogging. Therefore, the average infiltration rate for the pond continued to increase despite the fact that the inner part of the pond was clogging. We note that the mass balance estimate presented here does not contain an error estimate. We do not anticipate, however, that the errors in the calculation would be large enough to account for the disparity between the two measures; for example, it would require a error factor of four in the pumping rate to explain this discrepancy.

The diurnal temperature change in a body of surface water can produce a thermal signal that provides a way of monitoring
the infiltration of surface water into the subsurface. In this study, we have demonstrated the value of using wavelet analysis to isolate and analyze the signal associated with this diurnal forcing. The approach that we used is ideally suited for analysis of nonstationary signals and thus is an effective way to analyze temperature data or, as in our case, resistivity data. One important issue that requires further work is an improved understanding of the uncertainty in the derived estimates of infiltration rates. Our inversion algorithm incorporates a data weighting term and, from this, error estimates of infiltration rates; however, the value of these error estimates is predicated on our ability to assess actual data errors. Given this issue, the error estimates of the infiltration rates must be viewed with caution. In this work, we have only considered error from the sampling intervals; there are, however, two other sources of error that could be considered. First, calculating phase in the wavelet domain introduces error in a complicated way that is dependent on the (i) nonstationarity of the signal under consideration, (ii) the intrinsic noise in the measured signal, and (iii) the range of wavelet periods that are considered. The second type of error we have not considered is modelization error introduced when transforming calculated lag times into infiltration velocities. In this study, the modelization assumptions include: (i) inverting for a one-dimensional thermal velocity as a function of time and (ii) the use of the Hatch et al. (2006) model to convert the thermal velocity to an infiltration rate. One approach for ascertaining the magnitude of these error sources would be to use synthetic modeling of the signal or system under consideration. Future work in this direction is necessary to avoid overly optimistic error estimates.

The key finding of our study is the presence of the diurnal temperature signal in resistivity data. A measurement of resistivity has a significant advantage over a measurement of temperature. A temperature measurement is a point measurement made at the location of the sensor. A resistivity measurement can be made using spaced electrodes that sample an undisturbed, or less disturbed, region of the subsurface. In the case of the probe used in this field experiment, the resistivity measurements sampled a region tens of centimeters from the probe, while the temperature measurements were made at the probe. It is very likely that fluid flow at the temperature probe was highly affected by the disturbance of the sediments during the emplacement of the probe. An appealing extension of this study is to investigate whether the diurnal temperature signal can be seen in resistivity data acquired using surface electrodes or cross-borehole arrays, thus providing a minimally invasive means of quantifying infiltration rates and variability throughout subsurface regions on the scale of tens of meters. This would provide a new, much-needed way of capturing information about spatial and temporal variation in infiltration processes.

Acknowledgments
This research was supported by funding to R. Knight from Schlumberger Water Services. We wish to thank Brian Lockwood, Mary Bannister, and others from the Pajaro Valley Water Management Agency. We also thank Andy Fisher, Andrew Racz, and Calla Schmidt, from UCSC, for providing us with the pond volume to area function used to calculate the mass balance infiltration rate.

References