Observing Heterogeneous Unsaturated Flow at the Hillslope Scale Using Time-Lapse Electrical Resistivity Tomography

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Understanding water partitioning and storage on mountain hillslopes is important for vadose zone hydrologic modeling, water balance calculations, and predicting landslides. Revealing the dynamics of unsaturated water movement through time remains challenging due to the scarcity of spatially continuous observations at dense time sampling intervals. We investigate heterogeneous vertical flow using time-lapse electrical resistivity tomography over a span of 2 yr and use seismic refraction to determine the bedrock location on a hillslope with snow-dominated hydrology. We expect that heterogeneities in vertical unsaturated flow are driven by highly conductive zones in soil structure and higher localized water content due to surface topographic depressions and a long-term sustained snowpack relative to other locations, resulting in increased water availability. The results show that vertical flow heterogeneity and partitioning to deep flow occurred under contrasting precipitation inputs. We determine that topographic and vegetation cover heterogeneities on the hillslope and snow accumulation exert control on the location of partitioning to deep flow, likely due to macropores, roots, boulders, and localized water availability. We conclude that the regolith–bedrock boundary has a slope reversal that allows water to accumulate to drive heterogeneous flow.

Abbreviations: DOI, depth of investigation; ERT, electrical resistivity tomography; SWE, snow water equivalence.

Water resources in many regions of the world are sourced from mountain snowpacks that melt during the spring and summer to feed rivers and recharge aquifers (Beven and Germann, 1982; Christensen et al., 2004; Kosugi et al., 2006). As snow melts, water may be directed downslope as overland flow or into the subsurface as unsaturated or saturated flow, ultimately returning to surface water, becoming lost to deep flow, being used by biological processes, or becoming stored (Cassiani et al., 2009; McNamara et al., 2005). The location and timing of water traveling through the vadose zone has implications for maintaining surface water flows throughout the dry summer season and plant water availability (Brooks et al., 2015). Herein, we describe the background of the hydrologic processes under investigation, explain the conventional hydrological approach, and justify the geophysical approach of our experiment.

Hydraulic Processes Description

To understand the location and timing of water traveling through the vadose zone, we must investigate unsaturated vertical flow, soil water storage, and preferential flow. These parameters and processes remain challenging to observe and quantify at the hillslope scale due to their heterogeneous temporal and spatial nature (Hinckley et al., 2014; Hooper, 2001; Kosugi et al., 2006; McGuire et al., 2005). Soil moisture (the measurement of soil water storage) plays a key role in a number of vadose zone processes. Water partitioning is defined as the subdivision of soil water into different zones of the subsurface that have varying hydrologic properties (Gerke et al., 2010). Soil water storage is the volume of water that remains in the vadose zone after incoming precipitation and
outgoing percolation, lateral flow, and evapotranspiration (Engda et al., 2016; Hillel, 2003). Antecedent soil moisture conditions affect the hydraulic conductivity and the infiltration rate of meltwater into the soils (Birkel et al., 2012). Heterogeneous vadose zone flow, driven by preferential flow paths, flow-limiting layers, and regolith structure, can cause variable travel time of water to depth at the hillslope scale. Deep flow is either vertical percolation below the bedrock–regolith interface, lateral subsurface flow below the vadose zone, or a combination of both (McNamara et al., 2005). Understanding the heterogeneity of subsurface flow is important in terms of travel time of water through the subsurface and the ultimate hydrograph response of a watershed (Botter et al., 2010; Rinaldo et al., 2011). These processes contribute to subsurface flow and connectivity and are important factors for hydrologic management and modeling (McNamara et al., 2005; Sidle et al., 2001; van Schaik et al., 2008).

Vertical unsaturated flow occurs as water moves between the land surface and the saturated groundwater zone. Vertical unsaturated flow systems can be controlled by gradients in unsaturated hydraulic conductivity, with wetter soils having higher unsaturated hydraulic conductivity and faster flow rates compared with that of dry soils (Hillel, 2003; Šimůnek et al., 2003). Organic matter orientation and vertical root structures create macropores that may facilitate fast movement of water vertically compared with matrix flow (McDonnell, 1990). Underlying bedrock fractures, which can drive subsurface flow when hydrologically active, also promote rapid water movement (Sidle et al., 2001). Previous studies observed slow vertical flow in dry antecedent conditions in areas with low hydraulic conductivity except in locations with vertical preferential flow (McNamara et al., 2005). Furthermore, these studies show that flow water creates a larger lateral expansion of the porous network by connecting macropores (Sidle et al., 2001; Tsuboyama et al., 1994).

After infiltration, water may be redirected to move laterally downslope. Lateral flow within the vadose zone can be linked with vertical unsaturated flow and is most commonly driven by subsurface permeability contrasts. Lateral preferential flow occurs when a soil horizon responds to a wetting event before the soil horizon above it due to lateral movement of water in the subsurface (Ward and Trimble, 2003). Past research in snow-dominated systems has shown that soil moisture is typically low during winter at the regolith–bedrock boundary, although after wetting during snowmelt infiltration the boundary can become hydrologically connected and lateral flow can begin (McNamara et al., 2005). The slope of the regolith–bedrock interface is also a driver for lateral flow; perched water tables can form on impermeable rock, and water can then laterally flow along micro-channels on the rock surface (Graham et al., 2010b; Noguchi et al., 1999; Sidle et al., 2001) or be directed downward through vertical fractures (e.g., Frazier et al., 2002). The fill-and-spill hypothesis suggests that bedrock topography may control lateral flow until depressions in the bedrock become saturated (the “fill”), and after a precipitation threshold has been met, water may “spill” over microtopographic relief in the bedrock interface, resulting in saturated lateral flow downslope (Tromp-van Meerveld and McDonnell, 2006a).

Classical Hydrological Approach Based on Intrusive and Local Measurements

A primary limitation related to our current understanding of hillslope-scale unsaturated flow processes is that observations are often limited in space, precluding observation of these processes throughout the full extent of the hydraulically active vadose zone. Current field methods for studying unsaturated flow processes involve invasive excavation techniques to map macropore locations and soil structure, tracers to map water distribution and movement (Rinaldo et al., 2011), and a wide variety of point measurements to measure soil moisture and hydraulic conductivity (Allaire et al., 2009). Soil moisture probes are often used to measure water content over time; however, the installation of these probes is difficult in rock-dominated areas and in deep soil profiles. Furthermore, point-scale measurements cannot capture spatial variability in soil moisture (Rimon et al., 2007; Zhou et al., 2001). Snowmelt-dominated hillslopes are less suitable for point measurements due to the spatial variability of snow melt infiltration as a result of topographic and vegetation cover differences (Seyfried et al., 2009). Unsaturated hydraulic conductivity, a main driver in preferential flow, is also typically characterized using point- (e.g., tension infiltrometer) and plot-scale (e.g., rainfall simulation) measurements and can be difficult to extend to the hillslope scale (Allaire et al., 2009). Dye tracer studies that stain preferential flow paths are used to determine the location, connectivity, and spatial variability of preferential flow paths (Anderson et al., 2008; Noguchi et al., 1999), although this method requires excavation that destroys the soil profile under investigation and is not practical to implement at a large scale. With all excavation methods, deep flow is poorly characterized due to the inability to access the subsurface. Additionally, these common methods often do not allow repeatability or daily monitoring especially by means of natural precipitation and snowmelt (Flury et al., 1994; Rimon et al., 2007; Zhou et al., 2001).

Geophysical Approach

Nonintrusive time-lapse geophysical tools provide an opportunity to characterize and quantify preferential flow processes. Time-lapse geophysical tools are advantageous because they isolate subsurface parameters of interest that can be linked to soil moisture and can semi-continuously image the subsurface (e.g., Vereecken et al., 2015). In particular, electrical resistivity tomography (ERT) is useful for monitoring soil moisture dynamics (Daily et al., 1992) and has been used frequently in a time-lapse capacity to investigate hillslope hydrological processes (Cassiani et al., 2009; Hübner et al., 2015; Leslie and Heinse, 2013; Thayer et al., 2018; Travelletti et al., 2012). For example, French et al. (2002) performed an experiment using tracers and cross-borehole ERT during a snowmelt season and concluded that preferential flow dominated the early stages of snowmelt and later transitioned to
uniform flow, although they do not represent a complete hydrologic season. Scaini et al. (2017) demonstrated integration of time-lapse ERT into an irrigation tracer experiment to measure infiltration on a plot-scale hillslope. Thayer et al. (2018) used ERT along surface arrays to monitor a rapid infiltration of snowmelt followed by the gradual drying of the subsurface on a glaciated altered mountain hillslope and showed evidence for substantial loss to deep saturated flow. Seismic methods may be used to inform interpretation of time-lapse ERT results, particularly for identifying bedrock location and variable slope (e.g., Befus et al., 2011; Miller et al., 1989).

Objectives

The objective of this study was to observe subsurface hillslope water vertical flow at a daily measurement frequency on a multiannual time scale to capture vadose zone hydrologic dynamics up to 5 m in depth. Although we recognize that lateral flow processes are important and of interest, we focus here specifically on vertical flow to constrain the scope of this study. We observed hydrological processes in all seasons with the focus on water partitioning, patterns of changing soil moisture, and vertical flow (Fig. 1) using noninvasive, time-dense geophysical measurements. The high sampling frequency used in this study allowed us to focus on heterogeneous flow paths during naturally occurring infiltration events. In total, these data were recorded and analyzed for 22 mo, including two seasonal snowmelt recharge events.

This study addressed two primary questions: (i) what controls the spatial occurrence of vertical heterogeneous flow across the regolith–bedrock interface; and (ii) how does the magnitude and timing of water input change heterogeneous vertical flow dynamics? To answer these questions, we integrate information about soil moisture conditions, snowpack distribution, textural sorting of the sediment, topographic differences, and the precipitation type and quantity with time-lapse ERT measurements. We hypothesize that vertical heterogeneous flow is caused by zones of high hydraulic conductivity related to soil structure, in combination with higher localized and sustained water content due to surface topographic depressions that focus infiltration. We expect that the geometry of the regolith–bedrock interface can drive spatial transitions between lateral saturated flow and partitioning to vertical deep flow.

Methods

Site Description

This study was conducted on an east-facing hillslope at an elevation of 2570 m asl in the Upper Crow Creek watershed in the Laramie Range, Wyoming (Fig. 2). The climate is semiarid and characteristic of high plains. During the observation period, the site had a mean annual air temperature of 3°C (range −23 to 18°C), including 228 d below freezing and 331 d above freezing based on observations at the nearby Crow Creek SNOTEL (NRCS Site no. 11045) (Fig. 3). Cumulative precipitation in the 2016 and 2017 water years was 680 and 540 mm, respectively (SNOTEL, Crow Creek).

The geology of the site consists primarily of the Sherman and Lincoln granites overlain by a regolith consisting of a thin sandy-loam type soil and saprolite (Carey and Paige, 2016). The Sherman granite is a reddish-orange, coarse-grained biotite hornblende granite, and the Lincoln granite is a red medium-grained biotite (Frost et al., 1999). These granites are comprised of subhorizontal fractures (Zielinski et al., 1982) and vertical fractures (Witherspoon et al., 1979). In the upland portion of our study area, large granite boulders are scattered across the ground surface originating from an outcrop immediately upslope.

The vegetation cover includes coniferous trees (Pinus ponderosa Lawson & C. Lawson) concentrated upslope, with the vegetation downslope consisting of primarily sagebrush (Artemisia tridentata Nutt.). The average slope is 20%. Rainfall simulation research at the same site found that the soils can withstand 300 mm h−1 rainfall intensities without producing surface runoff (Carey and Paige, 2016), indicating that the site hydrology is dominated by subsurface processes.

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![Fig. 1. Schematic showing hillslope water movement pathways and vertical flow conduits.](image-url)
Geophysical Methods

Electrical Resistivity Tomography

Electrical resistivity tomography surveys measure the resistivity of the subsurface by using an electrode dipole to inject direct current into the ground and using additional dipoles to measure the resulting voltage. The voltage is used to calculate resistance via Ohm’s law, from which the intrinsic physical property resistivity is calculated using inverse modeling (see Binley and Kemna [2005] for a detailed review of the physical principles). When measured over time, geologic properties (i.e., lithology, porosity) are assumed to be constant, whereas environmental properties (i.e., water content, temperature) vary; therefore, the time-lapse ERT measurement is well suited to imaging changes in unsaturated water content. Empirical relationships link resistivity to saturation, fluid chemistry, and porosity (e.g., Carey et al., 2017). Many studies have explored the challenges and uncertainties associated with predicting water content using ERT (e.g., Brunet et al., 2010; Michot et al., 2003; Yeh et al., 2002). It is generally understood that it is impossible to obtain precise parameter estimates distributed across any given ERT image, and there are inherent uncertainties with this approach.

In October 2015, we installed a 59-m-long ERT line (Line 1) with 1-m electrode spacing, parallel to the slope (Fig. 2), with the Lippmann 4-point light 10W earth resistivity meter (LGM). Electrode 1 was located downslope, and Electrode 60 was the furthest electrode upslope. Each ERT measurement used a current injection time of 200 ms and was repeated (i.e., “stacked”) four to six times. We used a Wenner electrode array, which maximizes...
the signal/noise ratio, and contact resistance was measured for all electrodes prior to each measurement. From October 2015 to November 2016, measurements were taken every 4 h. In November 2016, we added a 35-m ERT line (Line 2) with 1-m electrode spacing perpendicular to Line 1 (Fig. 2). The two lines intersect at Electrode 42 of Line 1 and Electrode 18 of Line 2. The ERT measurements along Line 2 were made using the aforementioned data acquisition settings. Line 2 was oriented with Electrode 1 at the southwest end and Electrode 36 at the northeast end. Due to the increased power demands of adding additional electrodes, the measurement frequency was reduced to 12-h increments.

The process of geophysical inversion finds a subsurface model of resistivity that adequately fits the measured resistance data as judged by the RMSE, which quantifies the difference between the measurements and the model. The ERT data were averaged daily and inverted using R2 software (Binley, 2015). Although not equivalent to reciprocal errors, stacking errors are readily available for every dataset and were therefore used to develop an error model to weight the inversion (Parsekian et al., 2017). A homogeneous starting model of 10^{2.9} \Omega \cdot m, the approximate mean of apparent resistivities, was used for the initial time step. For each inversion thereafter, the inversion was regularized to model the initial time step. Inversion parameters were held constant for each dataset. The baseline datasets were obtained during the dry seasons on 18 Oct. 2015 for Line 1 and on 20 Nov. 2016 for Line 2. Using dry seasons for baseline data allows for straightforward interpretation of decreasing resistivity during wetting.

We determined the depth of investigation (DOI) following Oldenburg and Li (1999), where varying starting model resistivities are used to identify model elements at depth that are insensitive to the measured data. Resistivity datasets were corrected for temperature using a thermistor positioned at a depth of 0.6 m (depth to refusal by auger) following Keller and Frischknecht (1966). We assumed this depth to be most representative of the temperature across any one resistivity profile with the least amount of diurnal temperature fluctuation from surface temperature changes. Temperature data gaps throughout the 2 yr of experimentation were estimated by applying measured seasonal temperature patterns. The relationship used to empirically convert resistivity to water content $\theta$ (Carey et al., 2017) is

$$\theta = 3.89 \rho^{-0.53} \quad [1]$$

where $\rho$ is the temperature-corrected resistivity value from soils from the same site. Each dataset of $\theta$ was then differenced from a baseline dataset to determine time-lapse changes in water content over the study period.

At each location, we divided the subsurface into four evenly spaced layers (0–1 m, 1–2 m, etc.) below the ground surface. Each layer was 4 m along the slope (i.e., ±2 m about the center of each location). Within these layers, we calculated daily average water content values. To calculate vertical flow rate, we identify the position in each zone of the ERT data where water content increases with depth between two subsequent time steps. Then, using the distance between the location of increasing water content relative the previous time step and the elapsed time, we determined the velocity of the wetting front. We compared soil moisture dynamics at three different locations along Line 1 for the duration of the study. The locations were at 30 m (downslope), 40 m (midslope), and 50 m (upslope).

**Seismic Refraction**

Seismic refraction is a noninvasive method used to map subsurface acoustic wave velocity and to estimate weathering front depths (Befus et al., 2011). A series of seismic source shots along
a line produces acoustic waves that are measured by a receiver array. The resulting travel time dataset is inverted to produce a tomographic image of subsurface velocity structure. Primary wave velocity \( V_p \) values of <0.7 km s\(^{-1} \) are commonly interpreted as disaggregated materials; however, velocity for these materials can be ≈1.0 km s\(^{-1} \) if compacted. We identify the regolith–bedrock boundary as having a \( V_p \) value of 1.2 ± 0.14 km s\(^{-1} \) (Flinchum et al., 2018), based on drilling to bedrock at a similar site 4 km southwest of the study site. We used a seismic refraction survey coincident with ERT Line 1 starting at 12 m (i.e., Electrode 13) to infer bedrock topography. The seismic survey was 47.5 m long with 96 geophones placed at 0.5-m spacing, a shot spacing of 2.5 m, and two 5-m offset shots at the ends to observe deep ray paths (Burger et al., 2006). The source was a 4.5-kg sledge hammer striking a metal plate. Depth of investigation of the seismic refraction survey was clipped based on ray path coverage at the bottom and geophone spacing at the top.

Additional Measurements

Soil Sampling

Soil samples for grain size analysis were collected from 15 boreholes at 0.25-m intervals to a maximum depth of 0.85 m (refusal) by hand augering (Fig. 2). Sampling bias likely occurred due the small size of the stones that could fit into the hand auger bucket and because we could not sample below refusal when the auger encountered large rocks. We used a portable rock coring drill (Shaw Tool) to install a shallow well (Well A) to a depth of 2.4 m; however, it did not intersect the water table at the time of drilling. To quantify textural sorting of the colluvium-controlled porosity as a function of slope position (i.e., distance from outcrop), we performed grain size analysis on 33 samples. Dry sieve analysis was used to determine grain size distribution. The sizes of the sieves used were 12,500, 4000, 2000, 500, 250, 125, and 63 μm. Gradistat (Blott and Pye, 2001) was used to analyze the data. The analysis did not include a differentiation between silt and clay because it cannot be determined by sieve analysis. We used the F-statistic (i.e., the ratio of mean square regression to the mean square error) to evaluate significance of the relationships between soil texture properties, depth, and distance from the outcrop.

Soil Moisture

Seven frequency-domain soil moisture probes (GS1, Decagon Devices) were installed by pushing directly into the walls of an upslope and downslope borehole positioned along Line 1 (Fig. 2). Probes were positioned at depths of 0.10 and 0.22 m in one hole and 0.23 and 0.45 depths in a second hole about 1 m away for the upslope location and at depths of 0.10, 0.22, and 0.50 m for the downslope borehole. These sensors were calibrated in the laboratory using soil samples collected from the site at similar depths following the manufacturer’s protocol. We found the temperature sensitivity of these sensors to be <0.007 m\(^3\) m\(^{-3} \)°C\(^{-1} \). Caution must be taken when comparing these soil moisture probe measurements with the ERT datasets due to the different sampling volumes and spatial resolution (Day-Lewis et al., 2005; Oberdörster et al., 2010).

Topography

The topography of the site (Fig. 2) was obtained from a lidar survey flown in 2015. The resolution of the lidar dataset is 2 m laterally and <0.02 m vertically (relative to calibration control points). In addition, we measured microtopography with a laser level (CST/Berger) along Line 1 at 0.5-m intervals (used for calculating the slope of the hillslope) and a focused, 4 m by 6 m grid at 0.25-m spacing around the intersection of the two ERT lines. The precision of the microtopography survey is ±0.01 m. Laser level microtopography was used for ERT and seismic inversion.

Snow Cover and Precipitation

Although we recognize that snow is heterogeneously distributed across the landscape, for the purposes of our investigation, at the locations where snowpack exists, we assume that the meltwater infiltrates equally into our hillslope. It is not within the scope of this study to determine causes of snow cover and melt heterogeneity. Snow cover was recorded and photographed during site visits throughout the 2 yr (representative photos of snow cover at the site are included in the Supplemental Material). To monitor the snowpack depth and density, snow water equivalence (SWE) measurements were made every 14 d throughout the winter months of 2017 using a Federal Snow Sampler (Rickly Hydrological Co.). The SWE measurements were made at 10-m increments across Line 1 (Fig. 2). We augment our snow survey observations with data from the SNOTEL Site Crow Creek (1045) site. We found that the Crow Creek SWE observations were biased, with our study site having 42% of the SWE at the SNOWTEL site. From this, we developed a correction factor to estimate daily SWE for the 2016 and 2017 water years based on the hourly SNOTEL data calibrated to our on-site observations. Liquid precipitation measured by this same SNOTEL site was also used to compare net values between the years of 2016 and 2017.

Results

Precipitation and Soil Moisture Dynamics

The dates of snowmelt for Years 1 and 2 of the study, estimated using SNOTEL data, were 13 May 2016 and 26 Mar. 2017, although two more snow storms occurred, one on 21 Apr. 2017 with snow melting 4 d later and the other on 18 May 2017 with snow melting 6 d later (Fig. 3a). During the 2016 water year, cumulative precipitation was 680 mm, which was 140 mm more than cumulative precipitation during 2017. The maximum SWE in 2016 was 110 mm, which was 50 mm more than maximum SWE in 2017 (Fig. 3a).

Soil moisture dynamics showed similar abrupt wetting pattern during both years (Fig. 3b, 3c) corresponding to the period immediately after daily mean air temperatures rose above 0°C (Fig. 3d). At the upslope sensor array on Line 1, the probes at 0.10 and
0.22 m responded first to snowmelt on 12 Feb. 2016, followed by the probe at 0.23 m on 13 Feb. 2016 and the probe at 0.44 m wets on 14 Feb. 2016. Due to battery failure, the wetting date for the upslope array during 2017 could not be determined. At the Line 1 downslope sensor array, the probe at 0.10-m depth responded first on 6 Mar. 2016, followed by 0.23 m on 12 Mar. 2016 and 0.50 m on 14 Mar. 2016. This same response was observed in 2017 with 0.10 m wetting on 11 Feb. 2017, 0.23 m wetting on 5 Mar. 2017, and 50 m wetting on 17 Mar. 2017.

Geophysical Structure from Electrical Resistivity Tomography and Seismic Refraction

Background resistivity (18 Oct. 2015) on Line 1 ranged from 101.7 to 103.6 Ω m, with resistivity generally increasing with depth. Two areas of high resistivity at depth are identified between 25 and 32 m as well as between 40 and 50 m along the line, with a slight decrease of resistivity between these two zones at 36 m and low resistivity throughout the near-surface and downslope of 15 m attributed to a clay deposit based on shallow auguring (Fig. 4a).

Line 2 is a shallower profile (shorter electrode array), with comparable resistivity to Line 1 at their area of intersection and to the near-surface resistivity of the site (Fig. 4b). The right-hand side of Line 2 between 18 and 36 m (Fig. 4b) suggests a laterally anisotropic two-layer subsurface, whereas the left-hand side of Line 2 (0–18 m) shows a more isotropic single-layer geometry. The Line 1 seismic refraction survey shows high velocities upward of 4.0 km s−1 >10 m deep interpreted as unweathered bedrock (Fig. 4c). At 40 m along the line, the regolith–bedrock boundary is ~4 m below the surface, indicated by the 1.2 km s−1 velocity contour of this regolith–bedrock interface determined locally by Flinchum et al. (2018).

Time-Lapse Electrical Resistivity Tomography

Before describing the time-lapse ERT results, we note the presence of a well-known time-lapse inversion artifact. We observe that deep areas of the profile—that likely do not vary hydrologically with time—appear as “drying” anomalies (i.e., negative change in θ). This artifact occurs when the actual resistivity decreases in the shallow subsurface and the calculated resistivity at intermediate depths appears to increase, even though the actual resistivity of the intermediate depths does not change (Carey et al., 2017; Clément et al., 2010). Furthermore, the smoothing effect will lead to underestimates of water content above the infiltration front. These artifacts are most prominent during the wettest parts of the year, when resistivity decreases near the surface, creating a sharp resistivity contrast with depth. For example, in Fig. 5a, during a relatively dry season soon after the baseline measurement, there is little change in subsurface wetness and no artifact is present. In contrast, Fig. 5b shows an early season snowmelt period where the vadose zone has become more saturated/conductive (0–2-m depth 20–40 m along the profile) and the deeper zone appears to have dried (2–6-m depth, 20–40 m along the profile). We believe that the deeper zone has not changed and that this apparent drying is an artifact. Therefore, we focus our interpretation and analysis on increased wetting trends given that our baseline measurement is in the dry season and most changes in water content in the subsurface should be increased. Using apparent resistivity values (see Supplemental Material) rather than inverted resistivities can avoid this artifact, but we choose to use inverted resistivity values to more accurately assign depth, following many recent time-lapse ERT studies (e.g., Mirus et al., 2009; Travelletti et al., 2012).

The time-lapse results presented in Fig. 5 are chosen to highlight several key hydrologic events: (i) the wetting during snowmelt; (ii) the maximum saturation; (iii) the onset of drying; and (iv) the return to annual baseline conditions. Figure 5a shows the hillslope moisture conditions immediately after the start of the measurement, indicating little change. Figure 5b shows elevated water content to depths of 2 m during the snowmelt season. The wetting trend continues through 23 June 2016, eventually exceeding the depth of investigation in the 0- to 15-m portion of the profile (Fig. 5c). Heterogeneous vertical flow can be clearly seen in Fig. 5c and 5d at 40 m along the line where elevated water content is present at all depths in contrast to up- or downslope. A maximum water content at 4-m depth of θ = 0.10 m3 m−3 was recorded on 28 May 2016 at the midslope location (40 m). On this same date, the measured water content at 4-m depth was θ = 0.039 m3 m−3 and θ = 0.052 m3 m−3 upslope (50 m) and downslope (30 m). This deep
The midslope wetting zone is the only area (within our DOI) where water is moving through unsaturated flow to depths deeper than 2 m, and we interpret this as evidence of preferential vertical flow. Soon after the peak water content on 28 May 2016, the soil moisture begins to decrease through the summer dry season (Fig. 5d). One year from the beginning of the measurement campaign (10 Oct. 2016) (Fig. 5e), the subsurface has returned to a similar state as the background conditions, although we observe an average decrease in water content across the hillslope ($\Delta \theta = -0.025$ m$^3$ m$^{-3}$). Figure 5f shows the start of wetting in Year 2, with a slightly drier condition throughout the vadose zone relative to the same time during Year 1 (18% drier on average; Fig. 5b). During 2017, the snowmelt wetting (Fig. 5f) follows a similar distribution pattern as Year 1, although the area of preferential vertical flow at 40 m along the line is 2% drier averaged across all depths at its peak on 14 June 2017. Figure 5h shows the moisture distribution in July 2017 holding a pattern similar to the same time during the previous year. For these resistivity measurements, RMSE values averaged 1.11, with the highest value being 1.25, indicating the data fit the model closely. In addition, contact resistances for the measurements were low, indicating good electrical contact between the electrodes and the ground.

To compare water content differences between Line 1 and Line 2, we reprocessed the Line 1 dataset to have a common baseline date in the fall of 2016 when Line 2 was deployed (i.e., 20 Nov. 2016). As expected, the profiles from Line 1 with a fall 2016 baseline (Fig. 6a1–6d1) showed the same wetting and drying patterns as the inversions of Line 1 with the 2015 baseline date (Fig. 5e–5h). As snowmelt began, water content increased on Line 2 along the surface of the profile and to a depth of about 3 m between 17 and 23 m (Fig. 6b2). This is comparable to the 2-m wetting front observed on Line 1 (Fig. 6b1). In this analysis, preferential vertical flow at the midslope peaked on 23 June 2017 (9 d later than Fig. 5) and is observed in Line 1 as the surrounding drying area, shown in red, recedes due to the wetting in that area (Fig. 6c1). Line 2 shows the lateral extent of wetting >15 m along the transect (Fig. 6c2).

At the upslope location, there was no observable increase in water content below 2 m depth during either snowmelt seasons (Fig. 7a1). Figure 7a2 illustrates that the maximum water content

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**Fig. 5.** Difference in water content since the first day of measurement: (a) beginning of campaign; (b) spring melt wetting; (c) peak of heterogeneous vertical wetting; (d) drying of soil during summer months; (e) water content difference after 1 yr; (f) spring melt wetting; (g) peak of heterogeneous vertical wetting; and (h) drying of soil during summer months.
measured in Layer 3 and Layer 4 is 80% less than the water content in Layer 1 and Layer 2 on 28 May 2016 (the last day of wetting during Year 1 before drying began). In contrast, at the midslope location, we observe an increase in moisture content at all depth intervals during both years (Fig. 7b1). The peak water content measured midslope in Layer 1 was on 28 May 2016 (Fig. 7b2) and on 14 June 2017 during Year 2 (Fig. 7b2). The depth-average peak soil moisture midslope during 2016 and during 2017 was 0.17 m³ m⁻³. The downslope location behaves similarly to upslope, with Layers 3 and 4 downslope showing no increase in water content during the spring season (Fig. 7c1). The water content measured in Layer 3 and Layer 4 was less than the water content in Layer 1 and Layer 2 on 28 May 2016 (Fig. 7c2).

Soil moisture content preceding the snowmelt season is calculated for 18 Oct. 2015 and 2016 by averaging the measured water content in all four layers. The average soil moisture content at the baseline times for each year in the midslope zone was 0.14 m³ m⁻³ in 2016 and 0.12 m³ m⁻³ in 2017, ~12% drier during Year 2. Upslope and downslope both had an average soil moisture preceding the snowmelt of 0.15 during 2016 and 0.12 during 2017, ~20% dryer during the second year.

The moisture content begins to increase midslope in Layer 1 on 11 Mar. 2016, with consecutive wetting of underlying layers (Table 1) and a calculated vertical flow rate of 0.055 m d⁻¹ (Table 1). The rate of wetting front progression during Year 2 was 0.034 m d⁻¹ (~38% slower than the previous year) with Layer 1 wetting on 19 Mar. 2017 and lower layers again wetting consecutively (Table 1). We also observed evidence of lateral wetting sequences, where downslope locations appeared to wet first, followed by mid-slope and finally upslope (Table 1; Fig. 7).

**Soil Physical Characteristics**

We correlated each sample’s textural composition, categorized as percent gravel, sand, and silt–clay, with distance from the outcrop using borehole sample averages (Fig. 8a) and depth (Fig. 8b). We found that average gravel percentage in each borehole increased with distance from the hilltop, whereas sand content decreased and silt and clay percentage was constant with distance (Fig. 8a) and depth (Fig. 8b). We also used the average d₅₀ grain size from borehole sediment samples to determine the relationship between colluvium texture and the distance from the upgradient source (Fig. 8c). Using an F statistic (MATLAB regress function), we show a
positive relationship that is statistically significant ($p = 0.032$) at the 95% confidence level between grain size and distance from the outcrop (Fig. 8c). A similar positive relationship between grain size and depth was also statistically significant ($p = 0.030$) at the 95% confidence level (Fig. 8d). Well A (Fig. 2) reached refusal at 2.3 m, with the resulting mud having an oxidized color and granitic origin. Soils at the 2.3-m depth were not analyzed because of ambiguity of the location of the sample and contamination from muddy slurry that resulted from drilling.

**Microtopography**

The microtopography survey was centered on the intersection of the two time-lapse ERT transects. Over the 3.5-m downhill distance, the change in elevation is 1 m, with geometry that focuses the water toward the center of the survey area, but no slope reversals were observed (see Supplemental Material).

**Comparison between Soil Moisture Probes and Time-Lapse Electrical Resistivity Tomography**

Wetting and drying dates derived using soil moisture probes and ERT did not coincide, likely due to the different support volumes, water content calibrations, and non-uniqueness of the ERT inversion. Additionally, the measured water content dynamics are considered to be relative changes in water content, and therefore the absolute values are not expected to precisely match across different sensor types. Furthermore, spatial and temporal evolution of pore water conductivity could not be directly measured, and therefore it could not be accounted for in the resistivity–water content model, thereby adding another source of uncertainty to absolute water content estimates. We only compared 2016 data due to intermittent power loss on both instruments during the 2017 snowmelt season. The deepest soil moisture probe, 0.44 m, at $x = 31.5$ m on Line 1 (“up” on Fig. 2) was used for this comparison, and the ERT soil moisture was the daily average of soil moisture in a 2-m-long by 0- to 0.4-m-thick zone centered at $x = 31.5$ m on Line 1. The dates of wetting were 20 Jan. 2016 based on the soil moisture probe and 17 Feb. 2016 with ERT. The soil 0.44-m-depth moisture probe reached a weekly averaged peak water content of $0.52 \text{ m}^3 \text{ m}^{-3}$ on 21 Apr. 2016, and the ERT moisture peaked at $0.42 \text{ m}^3 \text{ m}^{-3}$ on 8 Aug. 2016, a 35% difference. Although the different support volumes of ERT and soil moisture probes make direct comparison challenging, we attempted this comparison between the deepest soil moisture probes ($\theta_{\text{SMP}}$, 0.50 m and 0.44 m at 10 m and 31.5 m along the ERT line, respectively) and the average ERT-derived water content ($\theta_{\text{ERT}}$) across the top 1 m at the same locations. At the location 10 m along the line, both methods produced similar water content values, with $\theta_{\text{SMP}} = 1.16 \theta_{\text{ERT}}$ ($R^2 = 0.70$, RMSE = 0.065 $\text{ m}^3 \text{ m}^{-3}$). At the
location 31.5 m along the line, the two methods were less similar, with \( \theta_{\text{SMP}} = 2.69 \theta_{\text{ERT}} \) \((R^2 = 0.30, \text{RMSE} = 0.10 \text{ m}^3 \text{ m}^{-3})\). The differences between the two sensors appear to be in similar magnitude of water content and may be attributed to soil moisture probe calibration and ERT water content calibration as well as smoothing in the ERT inversion, which results in underestimates of water content. Additional comparisons between the ERT and soil moisture sensors can be found in the Supplemental Material. The timing response to wetting and drying events appears to be more similar (Fig. 3 and 7).

Determining uncertainty estimates on ERT-derived absolute water contents is difficult due to the possible errors arising during measurement, inversion, and petrophysical modeling. We may assume that measurement errors are small (i.e., resistance, electrode positions) due to high-quality resistivity instrument electronics and the ability to determine spatial locations with measuring tapes, differential global positioning systems, survey equipment, and lidar. The petrophysical model parameters are generally expected to have relatively small influence on soil water estimates; for example, a 10% error in one parameter should not cause errors >5% in soil water content (Brunet et al., 2010). The RMSE of the calibrated model (Carey et al., 2017) relative to measured water contents was 0.031 m\(^3\) m\(^{-3}\), indicating a good ability of the model to predict water content independent of temperature and pore water resistivity. Although we cannot independently or directly measure resistivity at depth to determine errors against our inverted ERT result, we can compare the modeled apparent resistivity against the measured value for each quadrupole. For our data, we see absolute value misfit errors of \( |\rho_{\text{obs}} - \rho_{\text{mod}}| \) = 0.0035\( \rho_{\text{obs}} \) a mean misfit of 4.17 \( \Omega \) m, and median misfit of 3.31 \( \Omega \) m. At our site, adding up each of these error sources results in the following uncertainties (\( \theta_{\text{unc}} \)) regarding water content values: \( \theta = 0.10 \text{ m}^3 \text{ m}^{-3}, \theta_{\text{unc}} = 0.037 \text{ m}^3 \text{ m}^{-3}; \theta = 0.20 \text{ m}^3 \text{ m}^{-3}, \theta_{\text{unc}} = 0.042 \text{ m}^3 \text{ m}^{-3}; \theta = 0.30 \text{ m}^3 \text{ m}^{-3}, \theta_{\text{unc}} = 0.046 \text{ m}^3 \text{ m}^{-3}; \theta = 0.40 \text{ m}^3 \text{ m}^{-3}, \theta_{\text{unc}} = 0.051 \text{ m}^3 \text{ m}^{-3} \).

A notable feature in the soil moisture probe timeseries is that the water content rapidly increases in the spring, remains relatively stable (“plateaus”) for several months, and then gradually decreases in the early summer (Fig. 3b, 3c). This pattern is present for all depths at both of our soil moisture sensor locations, with the exception of the 0.5-m depth at 10 m along the line (Fig. 3c), which has a more arc-like trajectory with a smooth increase, a smooth decrease, and no discernable plateau. A similar “plateau” pattern is present in the 1- and 2-m depths of the ERT water content time-series (Fig. 7) at the downslope and midslope locations (i.e., corresponding with the locations of the soil moisture sensors) as well as the 2-m depth of the upslope area (Fig. 7a); however, the 1-m depth of the upslope area shows a more arc-like pattern with no discernable plateau. We speculate that this behavior may be attributed to more lateral flow (e.g., clay layers) lower on the slope in the sagebrush meadow, in comparison to more highly fractured rock and tree root macropores higher on the slope. The possibility of lateral flow within the vadose zone on the lower portion of the slope could result in prolonged periods of elevated water content

Table 1. Subsurface vertical flow velocity (\( v_{\text{vf}} \)), timing, and initial (\( \theta_{\text{initial}} \)), maximum (\( \theta_{\text{max}} \)), and change in moisture contents (\( \Delta \theta \)).

<table>
<thead>
<tr>
<th>Location</th>
<th>2016</th>
<th>2017</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( \theta_{\text{initial}} )</td>
<td>( \theta_{\text{max}} )</td>
</tr>
<tr>
<td>Upslope</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Layer 1</td>
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<td>0.30</td>
</tr>
<tr>
<td>Layer 2</td>
<td>0.19</td>
<td>0.21</td>
</tr>
<tr>
<td>Layer 3</td>
<td>0.09</td>
<td>0.06</td>
</tr>
<tr>
<td>Layer 4</td>
<td>0.07</td>
<td>0.04</td>
</tr>
<tr>
<td>Average</td>
<td>0.14</td>
<td>0.15</td>
</tr>
<tr>
<td>Midslope</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Layer 1</td>
<td>0.12</td>
<td>0.14</td>
</tr>
<tr>
<td>Layer 2</td>
<td>0.19</td>
<td>0.24</td>
</tr>
<tr>
<td>Layer 3</td>
<td>0.15</td>
<td>0.21</td>
</tr>
<tr>
<td>Layer 4</td>
<td>0.09</td>
<td>0.10</td>
</tr>
<tr>
<td>Average</td>
<td>0.14</td>
<td>0.17</td>
</tr>
<tr>
<td>Downslope</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Layer 1</td>
<td>0.24</td>
<td>0.37</td>
</tr>
<tr>
<td>Layer 2</td>
<td>0.17</td>
<td>0.24</td>
</tr>
<tr>
<td>Layer 3</td>
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<tr>
<td>Average</td>
<td>0.15</td>
<td>0.19</td>
</tr>
</tbody>
</table>
moisture conditions before snowmelt, we could not determine a relationship between moisture conditions before snowmelt and observed heterogeneous vertical flow. This relationship was not found to be significant at the 95% confidence level ($p = 0.35$) from our dataset and analysis alone. Further sampling or analysis is needed to study the possible relationship.

**Location and Drivers of Deep Vertical Flow Pathways**

Next, we considered the spatial occurrence of vertical heterogeneous flow. The subsurface topography of the regolith–bedrock boundary interpreted from seismic refraction data varies in the three locations in the hillslope: $0.32 \text{ m}^{-1}$ slope at $x = 30 \text{ m}$, $-0.093 \text{ m}^{-1}$ slope at $x = 42$ to $46 \text{ m}$, and $0.035 \text{ m}^{-1}$ slope at $x = 55 \text{ m}$ (Fig. 2c). Previous seismic observations have observed similar bedrock slope reversals (Befus et al., 2011), although without time-lapse imaging information the implications for control on water movement were not apparent. Because lateral preferential flow occurs at subsurface hydrologic discontinuities (Lin and Zhou, 2008; Noguchi et al., 1999; Sidle et al., 2001; Tsuoyama et al., 1994; Wilcox et al., 1997), the slope reversal midslope from $x = 42$ to $46 \text{ m}$ may promote ponding of water at the regolith–bedrock boundary. In turn, pooling at the bedrock interface could promote increased vertical partitioning to deep flow at that location. Alternatively, the slope reversal at the bedrock interface may be an indication of where enhanced weathering has occurred along vertical fracture networks, and therefore percolation will be enhanced even in the absence of ponding (e.g., Frazier et al., 2002). In addition, lateral preferential flow occurs during saturated conditions (Weiler and McDonnell, 2007), supporting our hypothesis that flow along the slope of the regolith–bedrock interface led to subsurface pooling of water that drove heterogeneous flow and partitioning to deep flow. Figure 5c shows that flow at $x = 38$ to $42 \text{ m}$ continues vertically past the regolith–bedrock interface and percolates below the depth of investigation of our time-lapse ERT measurement ($\sim 6 \text{ m}$). Because it is not possible to account for spatiotemporal variations in pore water conductivity when converting resistivity images to water content, we must acknowledge the possibility that the deep preferential flow anomaly at $x = 38$ to $42 \text{ m}$ (Fig. 5c) is the result of contrasting pore water resistivity under saturated flow conditions rather than simply being a time-varying saturation increase within the flow path. The observed anomaly would be consistent with the expected addition of conductive pore water as solutes are flushed from stagnant pores by infiltrating snowmelt during spring melt (e.g., Campbell et al., 1995). Using this interpretation, the relatively lower magnitude of the deep flow anomaly (Fig. 5g and 5h compared with Fig. 5c and 5d) may be explained by the smaller snow input during 2017 in comparison with 2016 (Fig. 3a) that would have resulted in less pore water flushing. This scenario would not substantially change our overall interpretations because it is still evidence for preferential vertical water movement to deep flow paths.

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**Discussion**

**Annual Vertical Flow Heterogeneity**

By observing subsurface vertical flow movement during two seasons with different water inputs, we can begin to understand the controls on heterogeneous flow. Timing and quantity of SWE differed during the 2 yr of this study. These observations (Fig. 3) indicate that the increased water availability from snowmelt in 2016 resulted in faster flow rates by increasing the average unsaturated hydraulic conductivity of the soil (van Genuchten, 1980).

Although the observed precipitation was greater in 2016 than in 2017 (Fig. 3), the maximum observed soil moisture throughout the year averaged across all depths was similar in each layer for both years. Also, the average peak moisture content of $0.17 \text{ m}^3 \text{ m}^{-3}$ was the same for both years (Table 1). To offset the apparent imbalance between contrasting input water availability and similar maximum water content, the vertical flow rate midslope was 38% slower in 2017 than in 2016.

Soil moisture conditions before snowmelt and water availability are variables that affect the annual differences in preferential flow (Woods and Rowe, 1996). Based on slight differences of soil
Snow is more likely to accumulate and be protected from incoming solar radiation and wind beneath trees and in topographic depressions, resulting in locally higher water availability in this location (Seyfried et al., 2009). We found that increased vertical flow occurred at the same midslope location ($x = 38-42$ m; Fig. 5c), with similar calculated maximum water content both years (Table 1), and did not occur elsewhere on Line 1 even with varying annual precipitation and SWE totals. Although we do not have detailed measurements of snowpack distribution through time at the site, in general, snow remains longer in the upslope area around the trees, and patchy snow is present in the downslope sagebrush area.

Through soil textural analysis, we found that grain size and percentage of gravel in the top meter increased with distance from the hilltop (i.e., distance from outcrop), whereas sand and silt–clay decreased. If the zone of preferential vertical flow at the midslope location is driven by high surface soil hydraulic conductivity, we would expect a higher percentage of coarse-texture material in the location where water is partitioned to deep flow relative to elsewhere on the hill slope, although, based on Fig. 8, this appears to not be the case. We conclude that cobbles and boulders are a part of the subsurface structure throughout the hillslope and promote increased unsaturated hydraulic conductivity and act as flow paths even where larger grains such as gravel are not prominent. This interpretation is similar to findings by Ward and Trimble (2003) and Koch et al. (2009), who showed that boulders with pore spaces filled with a finer-grained soil resulted in local deep infiltration by having a higher unsaturated hydraulic conductivity.

We also consider the likelihood that macropores contribute to vertical flow. Macropore flow results in faster drainage and little to no interaction with the surrounding soil matrix (e.g., van Schaik et al., 2008). Based on interpretations from both orthogonal ERT lines (Fig. 6) and the seismic refraction data (Fig. 4c), the midslope area directing water to deep flow could represent a dense network of macropores from roots and bioturbation, boulders, fractures, or some combination of these. The water content midslope in Layer 1 is low relative to the top layers both upslope and downslope. This implies fast vertical drainage and that water is not able to accumulate in Layer 1, explaining the high water content midslope in Layers 2 and 3. Organic matter in the subsurface was not quantitatively measured, but the midslope pathway to deep flow is near a Pinus ponderosa tree, many Artemisia, and a Juniperus plant, allowing the possibility of deep roots (see Fig. 2 for locations of trees distributed more closely to the line at >35 m).

Weathering granite can retain the blocky structure of the fractured rock, resulting in increased hydraulic conductivity (Hencher, 2010). This is important because the regolith–bedrock boundary is at ~4 m depth midslope based on the $V_{s}^2$ of 1.2 km s$^{-1}$ contour (Fig. 4c), although water also infiltrated 2 m past this boundary in isolated zones (Fig. 5c), indicating that the bedrock does allow water to percolate to deep flow. If the bedrock hydraulic conductivity and water available for surface infiltration are assumed to be spatially constant, then we may assume a spatially constant, though likely temporally variable, rate of movement to deep flow (e.g., Flint et al., 2008). Alternatively, if the bedrock is heterogeneously fractured with vertical joints, vertical flow can be expected in isolated areas (e.g., Frazier et al., 2002). Given the widespread presence of linear vertical fracture patterns in outcrops across the Laramie range (e.g., Blackstone, 1973), we infer that similar vertical fractures are also present in the subsurface, acting as conduits for vertical water partitioning below the soil.

Fate and Implications of Water Partitioned through the Deep Flow Pathway

The fate of the water leaving our experimental hillslope through partitioning to deep flow is an open question because we do not have a direct way of tracking water that we observe leaving the extent of our geophysical imaging. There appear to be three possible deep flow pathways: (i) water travels toward a groundwater spring ~50 m to the south of the observed deep flow path (e.g., Katsuyama et al., 2005); (ii) water continues traveling downgradient following the topographic slope to the east southeast and reemerges as diffuse surface flow (e.g., Shabaga and Hill, 2010); or (iii) water takes a much deeper path and leaves the vicinity of this hillslope altogether, ultimately reemerging as streamflow or directly contributing to recharge of the granite aquifer (e.g., Graham et al., 2010a). Future groundwater tracer tests may be useful for testing these hypotheses (Jones et al., 2006).

Discrete pathways to deep flow are rarely observed in the subsurface of hillslopes in part because point-sensors are depth limited and produce discontinuous observations and because we cannot measure everything everywhere. We speculate that, if this deep flow path was identified by chance, similar features may be common, particularly on weathering granite terrains where fracture networks can be observed in outcrop that likely are representative of subsurface fracture networks. Therefore, this may be a water balance loss component that is not typically accounted for due to a lack of available measured evidence (e.g., Sophocleous and Perkins, 2000). For example, water balance studies at the catchment scale may assume impermeable bedrock that allows zero deep percolation (e.g., Flerchinger and Cooley, 2000), possibly resulting in storage calculation errors. This has implications broadly for understanding how elements of the hydrologic cycle move water: if portions of the measured input are incorrectly accounted for, a difference-based water budget will end up with a remainder that is not representative of actual water transport or storage.

Time-Lapse Geophysics for Hillslope Hydrology

Our time-lapse ERT dataset is uncommon for studies of naturally occurring hillslope hydrologic processes because it spans nearly two water years and includes two snowmelt seasons at a nearly daily measurement interval (except for limited data gaps). Previous work has either used a more sporadic measurement interval (e.g., Hübnner et al., 2015; Miller et al., 2008), only observed isolated hydrologic seasons at high sampling rate (e.g., Thayer et al., 2018), or monitored controlled hydrologic inputs (e.g., Cassiani et al., 2009). We argue that there are two key
reasons why a daily measurement interval is essential for accurately representing hydrologic processes: (i) hydrologic processes may be unexpectedly triggered or may occur sporadically, so irregular or sparse measurements can miss important events, and (ii) geophysical datasets may be affected by noise, measurement errors, and uncertainty, so the availability of repeated datasets over time allows for increased data averaging and improved signal to noise. Although our sub-daily ERT imaging interval is considered high for geophysical observations, it is still sparse in comparison with soil moisture probes that obtain measurements at sub-hourly intervals. Therefore, we recognize that the geophysical measurements may miss very rapid hydrologic events, although seasonal trends should be reliably observed.

There is also value in time-lapse ERT imaging vs. soil moisture probes because the geophysical imaging can observe transects tens to hundreds of meters in size in a semicontinuous spatial manner, and the imaging can be designed to observe depths far below where direct sensors can be placed (Brunet et al., 2010). Past studies have used extensive soil moisture probe arrays (e.g., Gevaert et al., 2014; Tromp-van Meerveld and McDonnell, 2006b) and have even coupled ERT measurements with subsurface dense sensor arrays (e.g., Hübner et al., 2015). The nature of two- or three-dimensional subsurface images allows for information to be gathered in a spatially continuous manner that cannot be achieved with probes, and the ability to retrieve information several meters or more below the subsurface is important for studying deeper flow components of groundwater systems. Future improvements on the time-lapse imaging of subsurface flowpaths may include spatial correlation analysis to identify patterns of change (e.g., Paasche et al., 2006), particularly to reduce the datasets for comparison when studying multiple hillslopes.

Finally, we highlight the excellent opportunity for leveraging the typical snowpack melt event as a geophysical tracer, where a large volume of water infiltrated into the vadose zone within the span of several weeks (e.g., Thayer et al., 2018). This pulse of water wetting a relatively dry soil matrix substantially enhances signal to noise and offers an ideal geophysical target to aid in tracking hydrologic flow paths.

**Conclusion**

We found that spatial occurrence of heterogeneous flow across the regolith bedrock interface is controlled by the morphology of the regolith bedrock interface that likely indicates the location of vertical fractures. Our surface morphology measurements cast doubt on the explanation that topography-driven infiltration is the main driver of the observed subsurface flow. Vegetation cover and localized snow accumulation may also influence the location of enhanced vertical flow by creating macropores and focused water inputs from snow drifts. These factors, in combination with macropores from boulders and roots from nearby trees in the area, are interpreted to result in the higher unsaturated conductivity noted in this area. The timing of water input resulted in different timing of subsurface water movement, whereas less water input volume appeared to result in less vertical flow to deep groundwater. We found that vertical unsaturated flow patterns observed using time lapse ERT were similar over two water years with contrasting soil moisture conditions before snowmelt. We observed subsurface vertical flow in the zone of deepest percolation to be about 38% slower during the 2017 water year that started with drier subsurface conditions than the 2016 water year.

**Data Availability**

All data used in this study may be accessed at the University of Wyoming Research Data Repository at https://doi.org/10.15786/m2m1gp (Parsekian et al., 2018) or through publicly available sources as noted.

**Acknowledgments**

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