Monitoring critically saturated conditions for shallow landslide occurrence using electrical resistivity tomography

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Abstract
Soil wetness is an important property in determining the variable disposition of hillslopes to shallow landslides. Recent studies have demonstrated the potential of in situ soil wetness information for landslide early warning. However, the spatial representativeness of in situ sensors may be affected by local heterogeneities of soil properties and hydrological processes, and their installation may be destructive. Electrical resistivity tomography (ERT) has been used in the past to estimate plot-scale soil moisture variation and may overcome these limitations. In this study, we installed and operated an automated ERT monitoring system on a landslide-prone hillslope in the Napf region (Switzerland). The system was operational during a period of 9 mo, and measurements were conducted at high temporal resolution and under different soil hydrological conditions. Electrical resistivity was measured along two perpendicular profile lines in Wenner–Schlumberger configuration at 0.25-m electrode spacing. Soil saturation was calculated by the Archie’s law and the parameters were fitted with colocated soil moisture sensors. Comparison of ERT-derived soil moisture with soil wetness from in situ sensors showed a good correlation, and infiltration properties critical for landslide early warning could be reliably reproduced. Further, analysis of spatial saturation variation revealed that ERT was capable to detect heterogeneities of soil hydrological process. Under highly saturated conditions, the reliability of the saturation estimation was affected by an increased number of faulty measurements and the spatial heterogeneity of the infiltration process.

1 INTRODUCTION

Landslides constitute a considerable natural hazard in mountainous regions all over the world and impose a strong socioeconomic effect on societies, as they cause large economic losses and thousands of fatalities every year (Dilley et al., 2005; Froude & Petley, 2018; Kjekstad & Highland, 2009). Shallow landslides triggered by the infiltration of rainfall or snow melt water are particularly dangerous due to rapid failure upon activation. As water infiltrates into the subsurface, soil saturation increases and groundwater or perched water tables may rise. In return, shear strength decreases below a critical threshold, eventually leading to a slope failure along a shear plane (Bogaard & Greco, 2016; Terzaghi, 1943).

Regional landslide early warning systems (LEWS) have shown to be a cost-effective measure to prevent fatalities or
damage to mobile goods by issuing warnings during times of increased landslide danger (Stähli et al., 2015). In the recent decades, they have become a prevalent landslide risk management practice (e.g., Baum & Godt, 2010; Guzzetti et al., 2007; Piciullo et al., 2018). Here, we focus on empirical LEWS, which statistically relate the temporal variation of environmental variables with observed landslide events (Guzzetti et al., 2020). In the past, empirical LEWS have often been based on exceedance thresholds of rainfall intensity, duration, or amounts, due to the vast availability of rainfall information and the direct relation to the landslide triggering process (e.g., Caine, 1980; Guzzetti et al., 2008; Segoni, Piciullo, et al., 2018).

However, using rainfall information alone may disregard the hydrological preconditioning of the ground, which is an important causal factor for the occurrence of landslides (Bogaard & Greco, 2016). Analysis of hydrogeological conditions during past landslide events using available soil hydrological information indicated that critical rainfall amounts for slope failure may be reduced if soil moisture levels are elevated, as was shown for example for several landslide events in 2005 in the Seattle area, USA (Baum & Godt, 2010), or a series of events in 2018 in Pittsburgh, PA (Ashland, 2021). With a growing availability of soil wetness information, the performance of existing landslide forecast models could be improved after inclusion of soil hydrological data, for example, from in situ soil moisture measurements (Mirus, Becker, et al., 2018; Mirus, Morphey, & Smith, 2018; Thomas et al., 2020), from satellite observations (Abraham et al., 2021; Bordoni et al., 2021; Brocca et al., 2016), or from soil moisture simulations (Ponziani et al., 2012; Segoni, Rosi, et al., 2018).

Soil wetness measurements for the purpose of continuous monitoring are available at different spatial and temporal scales. At the point scale, volumetric water content (VWC) is estimated using electromagnetic sensors (time domain reflectometry, frequency domain reflectometry, capacitance-based), and soil water potential (SWP) is measured using tensiometers (Babaeian et al., 2019). Both monitoring techniques allow for soil wetness measurements at high temporal resolution. Although in situ sensors measure only a small volume of material, multiple sensor arrays at different depths are typically averaged to obtain a spatially integrated signal (Robinson et al., 2008). However, installation is laborious and costly, the soil column is disturbed during installation, and erroneous sensors are difficult to replace. Further, due to the small measurement volumes, which are in the order of several hundred or few thousand cubic centimeters, measurements may be affected by local-scale phenomena (e.g., preferential flow, root development around the sensor), which makes measurements difficult to compare (Jackisch et al., 2020). At the regional scale, soil moisture may be monitored by remote sensing techniques, for example, from satellite retrievals that are limited to near-surface soil moisture only, or from land-surface models that often assimilate satellite retrievals and cover greater depths (Reichle et al., 2017). Although satellite-based soil moisture estimates were shown to be useful for identifying landslide-prone conditions (e.g., Felsberg et al., 2021; Zhao et al., 2020), their use in a LEWS is limited by the coarse spatial resolution, by the reduced temporal resolution, and by the shallow sensing depth and assimilation model uncertainties (e.g., Thomas et al., 2019).

Geophysical methods (electrical resistivity, ground penetrating radar, electromagnetic induction) provide nondestructive measurements of ground properties at the meter to decameter scale and may be operated at high temporal resolution. Electrical resistivity tomography (ERT) measures the two- or three-dimensional distribution of electrical resistivity along one or several profile lines of electrodes, which may be placed at the soil surface or in boreholes. Pairs of electrodes are used to inject electrical current into the ground and to measure the potential difference, from which electrical resistivity is calculated (Samouelian et al., 2005). Electrical resistivity in the ground is mainly influenced by the lithology (nature of the solids and pore-space geometry), water content, pore water fluid resistivity, and ground temperature (e.g., Lesmes & Friedman, 2005). Single measurements are therefore mostly used for subsurface characterization, whereas repeated measurements at the same profile line (time-lapse tomography) are used to analyze time-variant processes in the subsurface (Perrone et al., 2014). In this respect, ERT was used to directly relate resistivity changes to changes in the soil water content (e.g., Jodry et al., 2019; Mirus et al., 2009; Nijland et al., 2010; Travellletti et al., 2012). Further to that, VWC can be estimated directly from resistivity measurements by using specifically calibrated petrophysical relations, derived from laboratory experiments (Brunet et al., 2010; Chambers et al., 2014; Hübner et al., 2015) or from field measurements (Fan et al., 2015; Kotikian et al., 2019; Pellet et al., 2016). Lehmann et al. (2013) derived a wetness index from the resistivity measurements and related its spatiotemporal variation to

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**Core Ideas**

- In situ soil wetness monitoring is used for landslide early warning.
- Electrical resistivity tomography (ERT) is a non-invasive alternative to sensors for soil moisture estimation.
- Spatial variation of soil hydrological processes can be assessed using ERT.
- Temporal soil moisture variation can be well reproduced at high temporal resolution.
- Data quality depends on the water saturation and the petrophysical function parametrization.
the triggering of a shallow landslide. Although ERT measurements are usually conducted manually, automated resistivity monitoring has proven to be a valuable tool to obtain repetitive measurements, for example, if high frequency of measurements is required to monitor specific processes at regular time intervals (Chambers et al., 2015; Keuschnig et al., 2017; Kuras et al., 2009), or if access to remote field sites is difficult and costly (Hilbich et al., 2011). Challenges include setting up a reliable system, the automated data-processing of the two-dimensional dataset, and maintaining long-term data quality (e.g., sustaining contact resistance, maintaining the equipment).

In a previous study in Switzerland, Wicki et al. (2020) demonstrated that the temporal soil moisture variation from in situ sensors at the point scale is a good proxy for the variable landslide danger at the regional scale. The antecedent saturation prior to a precipitation event and the amount of saturation increase during infiltration were identified as the most important statistical properties to identify critical soil hydrological conditions for landslide triggering. However, the quality of the landslide forecasts was limited by inhomogeneities of the long-term monitoring series (caused by faulty sensors that are difficult to replace due to the destructive nature of the method) and the effect of local-scale soil hydrological processes on the obtained signal as single profiles with few sensors were considered only. These limitations could potentially be overcome by the use of ERT measurements. The question arises: can the relevant statistical properties for landslide prediction be reliably reproduced by ERT? Further, can the reliability of predictions be sustained even under highly saturated conditions during which landslides occur? Finally, what is the added value from the higher measurement volume?

To answer these questions, a landslide-prone hillslope in Switzerland was equipped with ERT profile lines, in situ soil moisture sensors, and tensiometers, and soil wetness variation was measured over the turn of 9 mo. Statistical properties to identify critically saturated conditions for regional landslide activity were calculated and compared among the three monitoring techniques. Here, we focused on the installation and reliable operation of an automated ERT monitoring system to conduct measurements at a high temporal resolution, the calculation of VWC and saturation from resistivity tomograms using a field-derived petrophysical function, and the quality assessment of the resulting saturation estimates specifically under highly saturated conditions.

2 | MATERIALS AND METHODS

2.1 | Study site

The study site is located in the Napf region (Switzerland), which is part of the Swiss pre-Alps (Figure 1a,b). The landscape is dominated by narrowly incised fluvial valleys and steep hillslopes, which reach elevation up to 1,404 m asl (Napf peak). Climatological yearly mean precipitation reaches 1,500–1,700 mm in most of the Napf region. Precipitation falls throughout the year with a peak during the summer months when intense orographically induced thunderstorms may occur (MeteoSwiss, 2022). The monitoring site is located near the town of Wasen on a 30° hillslope facing southeast at an elevation of 920 m asl (Figure 1c), and the plot is covered by grassland vegetation. The location was chosen as it represents a typical hillslope prone to shallow landslides in the region, confirmed by reports of previous landslides by local residents (A. Winkelmann, personal communication, 2018).

The regional geology mainly consists of polymict conglomerates (Nagelfluh) with interbedded sandstone and marlstone and is part of the upper fresh water molasse (OSM) of the Napf formation (Wanner et al., 2019). At the monitoring site, the bedrock is overlain with a shallow layer of quaternary sediments (talus) with soil formation on top. Hand auger drilling indicated that the depth to bedrock is between 1.5 and 2 m at the location of the ERT profile lines; however, bedrock reaches the surface at some locations on the hillslope. Analysis of soil samples taken during the installation of the in situ sensors showed that the soil is rather fine grained and corresponds to the USDA soil type sandy loam (0.12-m depth) and loam (0.46- and 0.85-m depth, Table 1). An increase with depth was found for both clay content (6.0% at 0.15-m depth, 7.6% at 0.45-m depth, 10.9% at 0.90-m depth) and bulk density (1.36 g cm⁻³ at 0.15-m depth, 1.49 g cm⁻³ at 0.45-m depth, 1.72 g cm⁻³ at 0.90-m depth). Gray and rusty stains, which are a typical indicator for wet conditions (Vasilas et al., 2018), were visible from 0.50-m depth downwards.

2.2 | ERT monitoring

2.2.1 | Data acquisition

Two ERT profile lines were installed on the plot (Figure 1c), with one running perpendicular to the slope direction (horizontal profile) and the other running parallel to the slope direction (vertical profile), which allows the assessment of the spatial variation of hydrological processes and lithological heterogeneity on the plot scale. Each profile line consists of 48 electrodes equally spaced at 0.25-m distance, which was chosen to resolve small scale soil hydrological processes while still covering the entire soil cover (uppermost 2 m). Rod electrodes of 25-cm length and 0.8-cm diameter and were placed roughly 10 cm into the ground, which was found sufficient as the contact resistance remained low throughout the study period (<20.0 Ω). Data acquisition was performed using a Syscal Junior (Iris Instruments). Measurements could be programmed and accessed remotely through a field laptop that
FIGURE 1  (a) Map of Switzerland showing the location of the Napf region, (b) extract of the Napf region showing the location of the monitoring site, and (c) detail map showing the locations of the electrical resistivity tomography (ERT) profile lines (red, blue) and soil wetness sensors (yellow). Copyright by Federal Office of Topography Swisstopo, Wabern, Switzerland, reprinted in accordance with the open government data of Swisstopo [https://shop.swisstopo.admin.ch/en/products/free_geodata]

TABLE 1  Textural fractions, the corresponding USDA soil classification and bulk density of the soil samples, which were collected at the soil pit where the sensors were installed. The depths refer to the projected ERT depths

| Depth (m) | Clay (<2 μm) | Silt (2–50 μm) | Sand (50–2,000 μm) | USDA class | Bulk density (g cm⁻³) |
|----------|--------------|----------------|-------------------|------------|---------------------|
| 0.12     | 6.0          | 47.4           | 46.6              | Sandy loam | 1.36                |
| 0.46     | 7.6          | 48.1           | 44.3              | Loam       | 1.49                |
| 0.85     | 10.9         | 49.4           | 39.7              | Loam       | 1.72                |

was connected to the Syscal Junior using the Comsys Module. The system was powered with electricity from the grid.

The measurements were conducted in Wenner–Schlumberger configuration, which provides similar sensitivity to both horizontal and vertical structures (Samouëlian et al., 2005). A measurement of all 529 datum points took roughly 40 min to be completed. This permitted to compare the ERT measurements with the soil wetness monitoring data that was measured at 10-min resolution and aggregated to hourly values (see Section 2.3). The ERT measurements were taken daily at 9:00 a.m. CET, and the measurement frequency was increased to up to one measurement every 2 h during precipitation or snow melt events.

Because the Syscal Junior allowed to connect only one profile at a time, the two profile lines were monitored during two separate periods (Table 2). Between 11 Mar. 2020 and 7 July 2020, 259 measurements were conducted at the horizontal profile line. After, the vertical profile line was measured from 7 July 2020 until 31 Dec. 2020, and 336 measurements were conducted. Measurements continued thereafter; however, snow pressure in early 2021 led to the dislocation of electrodes and damage to cables, hence the data was disregarded from this point onwards. Apart from this, the system worked very reliably and without disruptions.

2.2.2  Filtering

Raw ERT data were filtered to remove erroneous measurement points or outliers. In a first step, datum points for which repeated measurements (with three maximum stacks)
showed a deviation of >5% were removed. Second, outliers were removed manually. Here, we removed datum points with apparent resistivity \( \rho_{\text{app}} \leq 0 \, \Omega \text{m} \) (outside physically possible range) and \( \rho_{\text{app}} > 1,000 \, \Omega \text{m} \). Based on the analysis of all apparent resistivity datasets, datum points with \( \rho_{\text{app}} > 1,000 \, \Omega \text{m} \) can clearly be regarded as outliers or measurement errors. Finally, datum points were removed that significantly deviated from the depth level mean resistivity. The deviation from the depth level mean resistivity, \( \Delta \rho_{\text{app}} \), was calculated for each datum point as follows:

\[
\Delta \rho_{\text{app},n} = \frac{\rho_{\text{app},n} - \rho_{\text{app},n,\text{mean}}}{\rho_{\text{app},n,\text{mean}}}
\]

where \( \rho_{\text{app},n} \) is the apparent resistivity at quadrupole \( x \) and depth level \( n \) from the mean of depth level \( n \), \( \rho_{\text{app},n} \) is the apparent resistivity at quadrupole \( x \) at the depth level \( n \), and \( \rho_{\text{app},n,\text{mean}} \) is the mean apparent resistivity at depth level \( n \). Here, we removed datum points with \( \Delta \rho_{\text{app}} > 0.8 \), a cutoff value that was determined manually from visual inspection of the distribution of all \( \Delta \rho_{\text{app}} \) values. The overall number of filtered datum points was low and amounted to 2.8% of all datum points at the horizontal profile and 1.8% of all datum points at the vertical profile. The number of filtered datum points varied over time (Supplemental Figure S1) and along the profile lines (Supplemental Figure S2). Hence, we attribute erroneous measurement points mostly to variation in contact resistance of single electrodes or damage of individual cable strings.

### 2.2.3 Temperature correction

Ground temperature variation significantly affects electrical resistivity, which is important to consider particularly if small resistivity changes or resistivity changes over long time periods are quantified (Hayley et al., 2007). Temperature correction of ERT datasets is often conducted after inversion of raw resistivity data (e.g., Brunet et al., 2010; Chambers et al., 2015; Fan et al., 2015; Jodry et al., 2019). Hayley et al. (2010) demonstrated that temperature correction prior to inversion may yield superior results and proposed a method in which the correction terms are derived from forward simulations. Here, we applied a simpler approach in which apparent resistivity values were corrected directly with weighted temperature fields.

The temperature correction was conducted in three steps (a detailed description of the mathematical formulations is given in the section “Temperature correction” of the supplemental material).

1. Ground temperature variation was estimated at each depth level of the apparent resistivity measurements. Between 0.00- and 0.87-m depth, ground temperature data was interpolated from nearby installed tensiometers (Figure 1c), which were installed in a soil profile at four depths (for more details see Section 2.3). Below that, temperatures were extrapolated by a sinusoidal function, following an approach used in previous ERT studies (e.g., Brunet et al., 2010; Chambers et al., 2014).

2. The temperature used for correction at each apparent resistivity depth level was calculated as the weighted mean temperature of all overlying depth levels, with increasing weight of layers closer to the surface (which constitute a higher relative volume due to the electrical current flowing in a half space).

3. Apparent resistivity measurements were corrected using an approach by Keller and Frischknecht (1966), which is commonly applied in temperature correction of ERT datasets (e.g., Brunet et al., 2010; Fan et al., 2015; Jodry et al., 2019; Mertzanides et al., 2020).

The spatiotemporal temperature evolution for both measured and simulated ground temperature shows large seasonal temperature variations at up to 2-m depth (Supplemental Figure S3), which remained positive throughout the study period, indicating that no soil freezing occurred. The effect of temperature correction on apparent resistivity values is significant, as shown for the first depth level in Figure 2a. The temperature correction can be validated by comparison with electrical resistivity measurements from in situ soil moisture sensors, where a similar event-scale variation is apparent and electrical resistivity values are in the same range (Figure 2b).

### 2.2.4 Inversion scheme

The inversion routine RES2DINV (Geotomo Software) was used to invert the apparent resistivity data (Loke & Barker, 1996). RES2DINV uses an iterative optimization algorithm that is based on a smoothness-constrained least-squares method and the goodness of fit of the obtained resistivity model with the measurements is quantified by the RMSE (Loke et al., 2003). Due to the large number of measurements

| Profile   | Period            | No. measurements | No. infiltration events |
|-----------|-------------------|------------------|-------------------------|
| Horizontal| 11 Mar. 2020–7 July. 2020 | 259              | 12                      |
| Vertical  | 7 July 2020–31 Dec. 2020 | 336              | 26                      |
| Total     |                    | 595              | 38                      |
(and the computational restraints), which include various processes over different time scales, and because we were interested in the quantification of extreme saturation events, we chose to invert datasets independently using the same inversion parameters for all measurements, rather than using a time-lapse inversion scheme such as applied in Travelletti et al. (2012). To account for small-scale soil hydrological processes related to the infiltration of water into the ground, the horizontal model cell size was reduced to half unit electrode spacing (0.125 m). Topography of the profile lines was measured by a differential GPS system and was considered in the inversion process. The inversion was iterated a maximum of five times or until percentage change in the RMSE between two consecutive iterations became \(<5.0\%\). The final iteration number used for further processing was determined manually for each dataset at the point where RMSE reduction became negligible. This typically occurred at the third iteration.

Mean specific resistivity across all measurements was relatively low at both profiles (range 100–400 Ω m) with values generally decreasing from the surface to deeper layers (Figure 3). Lateral electrical resistivity variation was higher at the vertical profile, which may be related to local lithological heterogeneities. Lowest mean specific resistivities (range 100–150 Ω m) were found at depths >1.00 m at the horizontal profile and at depths >0.80 m (partially >0.20 m) at the vertical profile. We explain this with an increase of the clay content at depth (e.g., Samouëlian et al., 2005) as observed in the soil samples analysis (Table 1), and by generally wetter conditions as indicated by higher SWP values at the lowest tensiometers (data not shown).

### 2.3 Soil wetness monitoring

In situ soil wetness sensors were installed as a vertical soil profile in proximity to the two ERT profile lines (Figure 1c). The VWC was derived from capacitance-based soil moisture sensors (5TE, METER Group). The sensors measure dielectric permittivity (DP) of the surrounding soil and VWC is calculated using a calibration function (Babaeian et al., 2019; Topp et al., 1980). The SWP was measured by tensiometers (T8 Tensiometer, METER Group), which consist of a water-filled rigid tube with a ceramic cup acting as a membrane. The water in the tube is exchanged with the surrounding soil and the resulting pressure change in the tube is measured by a pressure gauge (Livingston 1908). Both types of sensors were installed at four depths in direction of gravity (0.15-, 0.30-, 0.50-, and 1.00-m depth). Because the plot is sloped by 30˚, the corresponding ERT depths were projected trigonometrically and were thus defined to be at 0.13, 0.26, 0.43 and 0.87 m (referred to as “ERT projected depths”). At each depth, two sensor pair replications were installed to compensate for potential sensor defects.

The VWC values were normalized by estimated porosity at each sensor to calculate what is commonly referred to as “degree of saturation.” Fully saturated conditions were measured at each sensor location at some point during the monitoring period, as indicated by positive SWP values of colocated tensiometers. Hence, porosity was approximated as the 99.9 percentile rank VWC. The 99.9 percentile rank was chosen to reduce the effect of potential VWC outliers. The SWP was normalized, because during unsaturated conditions...
FIGURE 3  Mean specific resistivity (spec. res.) tomograms at (a) the horizontal and (b) the vertical profile. Black dots indicate the nearest locations of the soil wetness sensors, the black line indicates the 150 Ω m isoline, which was used as cut off for the calculation of the profile statistics, and blue dashed squares (A–F) indicate focus areas that were used for aggregation.

(i.e., negative pore water pressures), SWP values range on a logarithmic scale. Positive SWP values indicate the buildup of a (perched) water table and scale linearly. Here, we log-scaled SWP values ≤−1 hPa for the further analysis.

2.4 Soil moisture estimation

The petrophysical function used to relate electrical resistivity to VWC values is based on Archie’s law (Archie, 1942):

$$\rho = \rho_w \Phi^{-m} S^{-n}$$  (2)

where ρ is the specific resistivity, ρ_w is the pore water resistivity, Φ is the porosity, S is the saturation, and m and n are empirical parameters.

The pore water resistivity was constrained from in situ sensor data. Here, we applied an approach by Hilhorst (2000) with which the pore water electrical conductivity (EC) was calculated from bulk EC and bulk DP, both of which were measured by the soil moisture sensors (see section “Calculation of pore-water resistivity” in the supplemental material). The resulting temporal variation of pore water resistivity shows a large variation of values with depth but rather constant values over time, with two distinct decreases at the near-surface sensors during two sustained dry periods in April and June 2020 (Figure 4). For the fitting of the petrophysical function, we therefore used constant but depth-dependent pore water resistivity values (Table 3).

The porosity values Φ were taken from the saturation estimation (see Section 2.3) and ranged between 0.31 and 0.32 (Table 3). The fitting of the parameter values m and n was conducted following an approach by Pellet et al. (2016). We used a random set of 10,000 parameter combinations of m and n and compared ERT- with sensor-derived VWC. The m parameter was ranged from 1.3 to 3.0, and the n parameter was ranged from 0.1 to 4.0. The best parameter fit was chosen by the lowest RMSE between ERT- and sensor-derived VWC. Sensor-derived VWC was calculated as the mean VWC of the two sensor replications at each sensor installation depth. Electrical resistivity was calculated as the mean specific resistivity of all model blocks that were located within a depth band of 0.15 m around the four sensor installation depths, and they were integrated over the entire ERT profile line length.

The increase in clay content at larger depths may pose problems for the application of Archie’s law, which is reported to be valid for medium- to coarse-grained soils only (Samouëlian et al., 2005). Although other approaches exist that do consider the effect of electrical conduction along mineral surfaces such as the Waxman–Smits model (Waxman & Smits, 1968), here we excluded model blocks with very low specific resistivities from the soil moisture estimation (mean ρ < 150 Ω m; black isoline on Figure 3). This was motivated by the fact that these areas were limited to large depths where the fitting of
TABLE 3  Best parameter fits of Archie’s law (Equation 2) and corresponding RMSE and $R^2$ values of electrical resistivity tomography (ERT)-vs. sensor-derived volumetric water content (VWC) at the projected ERT depths

| Depth | Archie parameters | Goodness of fit |
|-------|-------------------|-----------------|
|       | $\Phi$ | $\rho_w$ | $m$ | $n$ | RMSE | $R^2$ |
| Horizontal profile |
| 0.13 | 0.32 | 29.5 | 1.70 | 0.96 | 0.015 | .84 |
| 0.26 | 0.32 | 29.2 | 1.74 | 2.48 | 0.005 | .87 |
| 0.43 | 0.31 | 35.8 | 1.52 | 2.80 | 0.004 | .71 |
| 0.87 | 0.32 | 9.6  | 2.50 | 3.20 | 0.006 | .03 |
| Vertical profile |
| 0.13 | 0.32 | 29.5 | 1.66 | 0.46 | 0.021 | .49 |
| 0.26 | 0.32 | 29.2 | 1.64 | 1.82 | 0.004 | .71 |
| 0.43 | 0.31 | 35.8 | 1.42 | 2.16 | 0.005 | .53 |
| 0.87 | 0.32 | 9.6  | 2.50 | 3.20 | 0.006 | .00 |

Note. $\Phi$, porosity; $\rho_w$, pore water resistivity; $m$ and $n$, empirical parameters.

the petrophysical function was further impeded due to a low temporal soil moisture variation.

2.5 Saturation statistics and infiltration events

For the analysis of the temporal soil wetness variation, profile mean and SD statistics were calculated from the ERT- and sensor-derived datasets. Periods of continuous water infiltration (in the following referred to as “infiltration events”) were then identified at each soil wetness time series based on the approach of Wicki et al. (2020). Infiltration events were defined as a continuous decrease in electrical resistivity, increase in saturation, and increase in SWP after a rainfall or a snow melt event. This event delineation permitted to quantify the infiltration event properties “antecedent saturation” (i.e., the saturation at the onset of infiltration) and “saturation increase” (i.e., the total saturation increase during periods of water infiltration), both of which were identified critical properties for regional landslide prediction (e.g., Ashland, 2021; Baum & Godt, 2010; Mirus, Morphew, & Smith, 2018; Wicki et al., 2020). In total, 38 concurrent infiltration events were identified during the study period (Table 2).

2.6 Observed landslide events

During the study period, a shallow landslide occurred in the night from 23 to 24 Dec. 2020, at 300-m distance from the monitoring site. Although the exact timing of the landslide was not known, it could be attributed to relatively moderate rainfall event with a total amount of 12.9 mm that accumulated over 11 h. The rainfall event was preceded by strong snow melt in the days before, observed by webcam images taken on site. Thus, the soil was highly saturated prior to the rainfall event. This landslide event permitted us to directly validate the potential of the different soil hydrological data to discriminate critical soil hydrological conditions for landslide triggering.
FIGURE 5  Temporal evolution of (a) daily air temperature and precipitation (prec.), (b) apparent electrical resistivity (app. res.) averaged over the first depth level, (c) volumetric water content (VWC), and (d) soil water potential (SWP). Black-gray bars indicate two sample infiltration events (INF1, INF2) and the date of the landslide.

3  RESULTS

3.1  Seasonal evolution of apparent electrical resistivity

Temporal evolution of the apparent resistivity averaged over the first depth level of each measurement showed distinct tooth saw patterns (Figure 5b), which can be related the drying and wetting of the soil when compared with air temperature and precipitation data (Figure 5a). Precipitation events were followed by sudden drops in apparent resistivity, which increased again thereafter at a slower rate in response to the outflow of soil water and the drying up of the soil. The largest resistivity increases and decreases were observed in the first part of the study period until mid-June 2020, during which two long periods of dry and warm weather occurred. Thereafter, until end of September 2020, precipitation events became more frequent yet less intense. Consequently, apparent resistivity values generally remained at a low level with a small temporal variation.

A similar but inverse pattern could be observed from sensor-derived VWC and SWP values at 0.13-m depth (Figure 5c–d), with both VWC and SWC increasing during precipitation events and decreasing thereafter. The relative magnitudes of the drying-out periods and the seasonal variation corresponded well with the temporal variation at the apparent resistivity time series. More pronounced value increases could be seen in the SWP time series in response to strong precipitation events, which is due to the ability of tensiometers to measure positive pore water pressures.

3.2  Specific electrical resistivity during infiltration events

The spatiotemporal evolution of specific electrical resistivity is illustrated for two sample infiltration events (INF1 and INF2, the timing is indicated on Figure 5), which were...
chosen as they constitute two significant wetting events and resulted in highly saturated conditions, and because ERT measurements at high temporal resolution were available. INF1 occurred beginning of June 2020, when a series of rainfall events (total rainfall amount of 58.2 mm over a period of 4 d, Figure 6a) led to continuous water infiltration after a 4-wk period of almost no rainfall. Electrical resistivity was measured at the horizontal profile (Figure 7a–g). The reference tomogram (Figure 7a) shows relatively high resistivity values near the surface, which can be related to dry near-surface conditions. After the onset of precipitation, electrical resistivity decreased starting from the surface and progressed to larger depths with time (progression of the wetting front). The largest decreases were observed near the surface (up to $-10\% \log \Omega m$) and the resistivity decreases reached depths of almost 1.0 m (Figure 7g). The corresponding profile mean specific resistivity values show a decrease of roughly $40 \Omega m$ (Figure 6b). Profile mean saturation and SWP derived from the sensors show a similar development (Figure 6c,d); however, the SWP increase was detected with a delay of 2 d.

The infiltration event INF2 occurred in mid-August 2020 (Figure 5). Although it was of shorter duration than INF1 and the total rainfall amount of 32.1 mm was smaller, pre-event saturation was higher (Figure 6e,g). This is visible by lower near-surface values of specific resistivity in the reference tomogram (Figure 7h). Again, electrical resistivity decreased from the surface and progressed to larger depths over time (Figure 7i–m). The resistivity changes reached largest depths in the upper part of the profile (up to 0.8-m depth), whereas resistivity decrease was limited to near-surface layers in the lower part of the profile. Relative resistivity decrease at INF2 was lower than at INF1 (up to $-4.5\% \log \Omega m$). Corresponding profile mean specific resistivity decrease amounted to $-15 \Omega m$ (Figure 6f). Profile mean saturation and
3.3 Volumetric water content estimation (petrophysical function)

As expected, specific electrical resistivity from ERT was negatively correlated with in situ measured VWC (Figure 8). However, the relationships differed significantly across the different depths and profiles, and therefore individual parameter fitting was performed. Best parameter fits indicate a similar range of fitted $m$ parameter values at both profiles for the uppermost three depth levels (range = 1.42–1.74 from 0.13- to 0.43-m depth). The fitted $n$ parameter values varied in a larger range with the near-surface layers inhibiting the lowest values ($n = 0.96$ at horizontal profile, $n = 0.46$ at vertical profile at 0.13-m depth) and became larger at 0.26- and 0.43-m depth (range = 1.82–2.80). At 0.87-m depth, automatic parameter fitting was not possible because the SWP increase happened simultaneously at the sensors (Figure 6g,h).
FIGURE 8 Specific resistivity (spec. res.) (electrical resistivity tomography [ERT]) vs. volumetric water content (VWC, sensors) at the four sensor installation depths with the point color indicating the number of filtered datum points from the respective apparent resistivity dataset. The $m$ and $n$ parameter values of the best Archie fit (Equation 2), as well as the corresponding graph of the Archie function, are plotted in red.

Temporal variation of both VWC and electrical resistivity was too low; therefore, fitting was conducted manually. The resulting $m$ and $n$ parameter values were considerably larger ($m = 2.5$ and $n = 3.20$ at both profiles). This may be explained by the increasing clay content at depth as shown by the soil samples (Table 1). However, due to the low observed value ranges, the corresponding parameter value uncertainties are substantial.

Comparison of ERT- and sensor-derived VWC shows a relatively good correlation for the near-surface layers (Figure 9; Table 3). Best correlations were found for the horizontal profile ($R^2 = .84$ at 0.13-m depth, $R^2 = .87$ at 0.26-m depth, and $R^2 = .71$ at 0.43-m depth). Correlations were lower for the vertical profile ($R^2 = .49$ at 0.13-m depth, $R^2 = .71$ at 0.26-m depth, and $R^2 = .53$ at 0.43-m depth). Although the drying out of the soil appears to be represented well, there were problems of over- and underestimation during periods of water infiltration (i.e., too low or too high VWC values after saturation increases) (Figure 9a–d). Very poor to no correlation was found at 0.87-m depth for both profiles ($R^2 = .03$ at horizontal profile, $R^2 = .00$ at vertical profile), although the RMSE was in a similar range as for the other depths (RMSE = 0.006 at both profiles).

Because the Archie parameter values $m$ and $n$ varied significantly with depth, we allocated each of them to the resistivity model blocks that were nearest to the respective sensor installation depth. The corresponding ERT-derived VWC and VWC change plots for the two infiltration events INF1 and INF2 are shown in Figure 10. The depth-dependent allocation of the Archie parameters resulted in a visible soil moisture transition between the different allocation layers (i.e., significantly drier or wetter than immediately above or below the transition), which is visible in both profiles but was most pronounced in the near-surface soil layer and at the horizontal profile (Figure 10a,h). Similarly to the plots of specific resistivity change, the progression of a wetting front is visible (Figure 10b–g, i–m). In contrast with Figure 7, the wetting front at larger depths was less visible. This may be related to the different Archie parameters applied at the different zones (i.e. lower $n$ parameter values near the surface caused a stronger VWC increase per Ω m decrease).

3.4 | Profile saturation statistics

The calculated profile mean saturation derived from ERT measurements shows similar temporal variability as the profile mean saturation calculated from all available soil moisture sensors (Figure 9e,j). Significant differences appear during periods of saturation increase, often showing an overestimation of the peak saturation. Further, from mid-October until the end of the monitoring period, considerable underestimation of saturation is visible. It must be noted that this period coincides with a higher number of missing datum points (Supplemental Figure S1). Direct comparison of ERT- and sensor-derived saturation values (Figure 11a,b) confirms that most of the variation could be reproduced by the ERT measurements. Comparison of ERT-derived saturation with sensor-derived SWP reveals a nonlinear relationship during highly saturated conditions (Figure 11c,d). Further, it is evident that during conditions with positive pore water pressures (i.e., above-saturated conditions), ERT-derived saturation was no longer sensitive to soil water pressure changes. Generally, largest spread of ERT-derived saturation values could be observed under highly saturated conditions. These conditions were also accompanied with the largest number of missing measurements. This points towards problems of data quality under saturated conditions.

Direct comparison of the ERT- and sensor-derived infiltration event properties antecedent saturation and saturation increase shows that they were generally well reproduced.
FIGURE 9  Temporal evolution (left panels) and scatter plots (right panels) of electrical resistivity tomography (ERT)- vs. sensor-derived volumetric water content (VWC) at the four sensor installation depths (a–e, f–i) and profile mean saturation (e, j)

by ERT (Figure 12). Comparison of antecedent saturation shows a robust statistical correlation between the two datasets ($R^2 = .76$, Figure 12a). Again, values scatter more at highly saturated conditions, thus decreasing the correlation under such conditions. The statistical correlation is better if the saturation change is compared ($R^2 = .91$, Figure 12b). It is apparent that saturation increase amounts at the ERT-derived saturation dataset were larger during periods of strong infiltration (i.e., dots below the dashed line), and they were less pronounced under periods of weak infiltration (i.e., dots above
the dashed lines). This is in correspondence to the findings that infiltration was generally overestimated during periods of strong infiltration.

The specific soil hydrological conditions of individual infiltration events become more evident if individual infiltration events are plotted in the antecedent saturation vs. saturation change space (Figure 13). The general distribution of infiltration events is similar at the ERT-derived dataset and the dataset derived from the soil moisture sensors. However, it appears that the ERT-derived infiltration events scatter more and plot more towards the outer envelope of possible value combinations (indicated by the dashed lines on Figure 13a,b). Further, some events appear outside the possible value range, indicating an overestimation of the saturation increase or antecedent saturation. As a consequence, individual critical infiltration events (such as the landslide triggering event “LS”) are less distinguishable in the ERT-derived dataset compared with the sensor-derived infiltration events therefore potentially limiting the ability to identify critically saturated conditions.
3.5 Spatial variability of ERT-derived saturation

The spatial variation of the ERT-derived saturation was assessed by comparing the profile mean saturation of three focus areas defined previously at each ERT profile (Figure 3). For this purpose, the Archie parameter fitting and VWC prediction procedures were applied to data subsets containing only the corresponding model blocks. Temporal variation of mean saturation was similar across all focus areas during most of the study period (Figure 14). However, during specific periods of time, the temporal evolution differed significantly (e.g., because short-term changes were significantly different or because the mean saturation differed). During some periods, values greater than 100% saturation were observed. These periods predominantly occurred during times of lower data quality (indicated with gray boxes in Figure 14), which show periods during which >20 datum points were filtered) and may thus be the result of inversion artifacts. Further, the exceedance of 100% saturation was only observed for focus areas at greater distance to the sensors (i.e., focus areas A, C and D). This may result from spatial heterogeneities of the infiltration process, causing a reduced representativeness of the in situ soil moisture sensors for the local-scale electrical resistivity variation measured by ERT.

The spatial saturation variability within a specific focus area can be analyzed by mean vs. SD plots. Further, the temporal evolution of spatial mean vs. SD saturation was shown to be a good predictor for the attainment of critical soil hydrological conditions for landslide triggering (e.g., Lehmann et al., 2013). In Figure 15, mean vs. SD pathways of individual infiltration events are plotted with the direction of progression indicated by arrow heads, and INF1 and INF2 are highlighted as solid lines. To reduce the effect of bad data quality, periods of increased filtered data points are not shown (i.e., gray areas in Figure 14). The expected pattern of SD decrease with increasing saturation (i.e., profile saturation becoming more homogeneous in the entire soil profile) was well reproduced by both ERT (Figure 15a,b) and the soil moisture sensors (Figure 15c). Generally, the spatial variability of ERT-derived saturation (expressed by the profile SD) was larger than that of the sensor-derived saturation, which can be attributed to the higher number of data points in the ERT dataset (i.e., all model blocks within a specific focus area) compared with the lower number of soil moisture sensors (i.e., 8 sensors). Further, the spatial variability between focus areas was larger.
**FIGURE 12** Electrical resistivity tomography (ERT)- vs. sensor-derived infiltration event properties showing (a) antecedent saturation (ant. sat.) and (b) saturation increase (sat. increase). The red dots indicate the two sample infiltration events INF1 and INF2 and the landslide event (LS). The statistical correlations are indicated by the respective RMSE and $R^2$ values.

**FIGURE 13** (a) Electrical resistivity tomography (ERT)-derived and (b) sensor-derived antecedent saturation (ant. sat.) vs. saturation increase (sat. increase). The red dots indicate the two sample infiltration events INF1 and INF2 and the landslide event (LS). The dashed line indicates the theoretical outer value envelope.

**FIGURE 14** Electrical resistivity tomography (ERT)-derived profile mean saturation aggregated over the six focus areas A–F (Figure 3). The Archie’s law (Equation 1) was fitted at each focus area individually. The gray boxes indicate periods of decreased data quality ($N$ filtered datum points > 20), and the black dashed lines highlight the two infiltration events INF1 and INF2 as well as the landslide event.
FIGURE 15  Profile mean vs. SD saturation (a, b) derived from electrical resistivity tomography (ERT) and (c) derived from the soil moisture sensors. The ERT-derived saturation was fitted and aggregated at the six focus areas A–F individually (Figure 3). The lines show the temporal evolution of all identified infiltration events and the flashes indicate the direction of evolution. The solid lines show the two sample events INF1 and INF2. Only measurements with \( N \) filtered datum points < 20 are shown at the vertical profile, which can be attributed to a more heterogeneous lithology (Figure 3). Both infiltration events INF1 and INF2 progressed towards the lower right end of the data distribution of each focus area, indicating the development of highly saturated conditions throughout the soil profile. Further, similar magnitude of the infiltration event pathways could be observed both across focus areas and between ERT- and sensor-derived saturation. Deviation from the general mean vs. SD pathways can be seen at individual focus areas and infiltration events (e.g., focus area C, Figure 15a), which may be attributed to the effect of inversion artifacts due to faulty measurements.

Comparison of the resulting ERT-derived infiltration event properties by focus area with the corresponding sensor-derived event properties shows that the general distribution was similar across all focus areas (Figure 16). Variation across focus areas increased towards high antecedent saturation and high saturation change values, and the deviation from the soil moisture sensors was larger for specific focus areas (e.g., focus areas C and D). This may be the result of different soil hydrological conditions along the ERT profile lines, which are more pronounced under periods of strong infiltration.

4 DISCUSSION

4.1 Characterization of critically saturated conditions

In this study, soil saturation dynamics measured by ERT were in good agreement with measurements from colocated soil wetness sensors. On a seasonal time scale, the timing and magnitude of drying and wetting events could be well reproduced. Focusing on periods of water infiltration, soil hydrological processes such as the progression of a wetting front at depth could be detected by the ERT measurements. Further, specific infiltration event statistics such as antecedent saturation and saturation increase could be reliably reproduced. Towards reaching saturated conditions (as indicated by positive SWP values from the tensiometers), electrical resistivity became constant, which was reported by other studies as well (e.g., Bai et al., 2013; Fan et al., 2015). We found indications for the spatial variation of the infiltration process, which may be related to local-scale variations of macropore flow (Beven & Germann, 1982), lithological differences such as the presence of impeding layers at variable depth to the surface (e.g. Sidle et al., 2000; Tani, 1997), or preferential flow along the hillslope during stormflow conditions (Weiler et al., 2005). Although this caused some variation in the derived infiltration event properties, most areas along the ERT profile indicated similar temporal saturation variation.

Here, we observed an increased number of filtered measurement points (i.e., faulty measurements) at highly saturated conditions. The faulty measurements might be due to technical effects such as water entering the cables (short-term effect) or due to damage to cable strings (long-term effect), for example, by rodent activity. Other influencing factors on short-term errors may include the fluctuation of electromagnetic fields due to water circulation near the electrodes (Keuschning et al., 2017). Previous studies have stressed that a changing number of measurement errors may considerably affect the comparability of subsequent measurements.
FIGURE 16  Electrical resistivity tomography (ERT)- vs. sensor-derived profile mean infiltration event properties showing (a) antecedent saturation (ant. sat.) and (b) peak saturation increase (sat. increase). The dot colors correspond to the focus areas A–F (Figure 3). The statistical correlations are indicated by the respective RMSE and $R^2$ values. Only measurements with $N$ filtered datum points $< 20$ are shown.

FIGURE 17  (a) Temporal evolution and (b) scatter plot of electrical resistivity tomography (ERT)- vs. sensor-derived profile mean saturation. Archie’s law (Equation 1) was fitted to specific resistivity datasets with $\leq 20$ filtered datum points in the respective apparent resistivity dataset. Omitted datasets are shown in gray.

(e.g., Keuschnig et al., 2017; Rosset et al., 2013). To assess the effect of reducing measurement errors on the long-term stability of our dataset, we conducted the Archie’s law fitting procedure on datasets with good data quality only (number of faulty measurements $< 20$, 75% of the dataset). As expected, the resulting saturation time series follows the sensor-derived profile mean saturation more closely (Figure 17a) and the statistical correlation is more significant ($R^2 = .85$ if smaller dataset is considered, $R^2 = .79$ if all data points are considered) (Figure 17b). This demonstrates the sensitivity of the predicted saturation to only small variations of the data quality. It is therefore important to identify and potentially reduce sources of measurement errors during the monitoring process. However, it was also found that the saturation estimation was poorer in areas along the profile lines that were at greater distance from the in situ soil moisture sensors. This was explained by the spatial heterogeneity of the infiltration process. The reduced spatial representativeness of the soil moisture sensors for the infiltration process at more distant locations may additionally explain the lower saturation prediction performance, particularly during periods of strong water infiltration.

Archie parameters were found to vary significantly with depth. Here, we attributed this mainly to the depth variation of soil properties (i.e., an increase of clay content and bulk density with increasing depth as confirmed by the soil samples analysis). Such a depth variation of soil properties is to be expected from a naturally developed soil with different soil horizons and layers (Phillips & Lorz, 2008), and resulting depth variation of Archie parameters was reported from other studies too (e.g., Hüblner et al., 2015; Mertzanides et al., 2020; Yamakawa et al., 2012). The fitted $n$ parameter values for the uppermost layers ($n = 0.96$ at the horizontal profile, $n = 0.46$ at the vertical profile) were considerably lower than
what would be expected from literature values. In other studies, the $n$ value was significantly higher ($n > 1.6$; e.g., Nijland et al., 2010; Pellet et al., 2016) or it was assumed as $n = 2$ (Brunet et al., 2010; Yamakawa et al., 2012). The $n$ parameter values changed only marginally ($n = 0.94$ at the horizontal, $n = 0.58$ at the vertical profile) if datasets with few measurement errors were considered only ($n$ filtered data points $< 20$, cf., Figure 17). We assume that the underestimation of $n$ parameter values at 0.13-m depth is due to the consideration of constant $\rho_w$ values. At this depth, $\rho_w$ decreased significantly during dry periods (Figure 4). As these data points constitute the dry end of the saturation distribution, this may considerably affect the $n$ parameter estimation. More generally, the parameter estimation of $m$ and $n$ can also be affected by our choice of not using an alternative formulation of Archie’s law that includes an additional fitting factor $a$, which can be seen as compensating for all sources of error not taken into account (Glover, 2016). In the absence of $a$ (= by setting it to 1), errors are compensated through the fitting of $m$ and $n$. Finally, the estimation of Archie parameters at greater depths may be considerably affected by to the increased clay content (10.9% at 0.85-m depth). Although models that account for higher clay contents were used in other time-lapse resistivity studies (e.g., Chambers et al., 2014; Lehmann et al., 2013; Uhlemann et al., 2017), we believe that the effect on the estimated soil moisture variation is limited in this study, as areas with very low mean electrical resistivities (i.e., mean electrical resistivity $< 150$ $\Omega$ m, presumably areas with high clay content) were removed from the process of soil moisture calculation.

4.2 Applicability of ERT in regional landslide early warning

In regional LEWS, point-scale soil moisture measurements are often used to infer information on the soil hydrological state within specific warning regions. To this end, soil moisture is commonly measured in the uppermost 1–2 m at carefully selected and representative monitoring sites (e.g. Mirus, Becker, et al., 2018; Thomas et al., 2020). In this study, ERT demonstrated to reliably reproduce critical statistical properties of the infiltration process that were identified previously to be valuable for predicting shallow landslides (Baum & Godt, 2010; Mirus, Morpew, & Smith, 2018; Wicki et al., 2020). However, the applicability may be limited by an increasing number of erroneous measurements towards highly saturated conditions (when most landslides occur), as observed in this study. In an operational context, soil wetness information is generally used to describe the antecedent wetness state of the soil only (which occur mostly under unsaturated conditions), whereas the landslide triggering conditions are inferred from more widely available rainfall information (Bogaard & Greco, 2016; Mirus, Morpew, & Smith, 2018). The effect of potential measurement errors towards saturated conditions may therefore be less relevant for the application in a regional LEWS.

Further, we showed that ERT measurements may effectively reproduce local-scale soil hydrological processes at depth, such as the progression of a wetting front. Such detailed information on the depth distribution of soil moisture (as opposed to the discrete information at different depth levels gathered from soil moisture sensors) was recently shown to be relevant for landslide prediction, for example, by describing temporally variable drainage conditions and the hydrological connectivity to the subsurface prior to precipitation events (Greco et al., 2021; Marino et al., 2021). Finally, the long-term inhomogeneity of monitoring time series from soil moisture sensors (e.g., due to defects of individual sensors or due to soil compaction after installation) was identified to limit the long-term application of in situ soil moisture sensors in regional LEWS (Wicki et al., 2020). In this respect, ERT may help overcome these limitations due to the non-invasive nature of this technique. Although this application was not analyzed explicitly in this study, it would be beneficial to repeat the measurements and the analysis at later times.

4.3 Methodological limitations

The results obtained in this study are constrained by several assumptions and methodological limitations. Regarding the monitoring setup, only one electrode configuration was tested (i.e., Wenner–Schlumberger). Different electrode configurations are more sensitive to vertical structures such as preferential infiltration along macropores (e.g., dipole–dipole configuration) and might thus provide additional information on spatially variable soil saturation (Garré et al., 2012). Further, the application of reciprocal measurements, which were not conducted in this study, could be used to assess data quality of apparent resistivity datasets and to improve data filtering and inversion (Koestel et al., 2008). Regarding inversion of apparent resistivities, no sensitivity analysis was performed for the chosen inversion parameter settings. A variation of the damping factor in particular could potentially affect the obtained spatial variation of electrical resistivity and resulting profile saturation values. A higher damping factor could reduce the effect of inversion artifacts, but at the same time may eliminate true spatial variability in hydrological processes (Loke & Barker, 1996). A methodological limitation remains the previously discussed fact that the spatial heterogeneity of the infiltration process may cause a misprediction of the saturation values along the ERT profile line. Finally, inversion artifacts could in general be reduced by using time-lapse inversion schemes (Loke, 2001; Loke et al., 2014; Perrone et al., 2014; Uhlemann et al., 2017), as opposed to inverting datasets individually as was done in this study. However,
time-lapse inversions were tested for selected infiltration events, which resulted in only slight reductions of the inversion artifacts and slight decreases of RMSE values (Supplemental Figure S5). Because these differences were only small and computational efforts would have been considerable, time-lapse inversion was not performed for the entire dataset.

5 | CONCLUSIONS

In this study, an automatic ERT monitoring system was installed and operated over a period of nine months at a landslide-prone hillslope in the Napf region (Switzerland), and electrical resistivity was measured under variable soil hydrological conditions and at high temporal resolution. The degree of saturation was calculated using Archie’s law, which was fitted in the field based on colocated soil moisture sensors, and infiltration properties commonly used to predict landslides were calculated. We found a good correlation of electrical resistivity with VWC and most of the temporal saturation variation measured by the soil moisture sensors could be reproduced by ERT. For the application of ERT monitoring in regional landslide early warning we draw the following conclusions:

• Critical infiltration properties and statistics commonly used to assess the temporally varying regional landslide disposition (i.e., antecedent saturation prior to infiltration, saturation increase during infiltration; temporal evolution of mean–SD pathways) could be reliably reproduced by ERT at high temporal resolution (up to every 2 h) and the spatial variation of these properties along the ERT transects could be quantified. Therefore, ERT could be used to complement other in situ soil wetness monitoring techniques used in in landslide early warning, particularly if the spatial soil moisture variation is of interest.

• The reliability of saturation estimation decreased towards highly saturated conditions due to an increase of erroneous measurements and due to spatial heterogeneities of the infiltration process. To improve the saturation estimation, influencing factors on erroneous measurements should be studied in more detail.

• Despite lithological heterogeneities at the study site, critical saturation properties could be reproduced equally well along and across the ERT profile lines. This indicates that calculating the degree of saturation (as opposed to using electrical resistivity directly) is a robust way to normalize ERT measurements across different lithologies.

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AUTHOR CONTRIBUTIONS

Adrian Wicki: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Validation; Visualization; Writing – original draft; Writing – review & editing. Christian Hauck: Conceptualization; Methodology; Resources; Supervision; Writing – review & editing.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

DATA AND CODE AVAILABILITY

The full raw ERT dataset is publicly available on the EnviDat repository (Wicki & Hauck, 2022).

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**SUPPORTING INFORMATION**

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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