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### Key Points:

- We test the efficacy of using Deep Learning to forecast subsurface hydrologic response for hillslopes that are prone to shallow landsliding
- The model produces pore pressure predictions for landslide-relevant conditions up to 36-hr in advance with as little as 6 months of data
- Our work encourages further exploration of machine learning as part of the development of landslide warning systems

### Supporting Information:

- Supporting Information S1

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## Deep Learning as a Tool to Forecast Hydrologic Response for Landslide-Prone Hillslopes

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**Abstract** Empirical thresholds for landslide warning systems have benefitted from the incorporation of soil-hydrologic monitoring data, but the mechanistic basis for their predictive capabilities is limited. Although physically based hydrologic models can accurately simulate changes in soil moisture and pore pressure that promote landslides, their utility is restricted by high computational costs and nonunique parameterization issues. We construct a deep learning model using soil moisture, pore pressure, and rainfall monitoring data acquired from landslide-prone hillslopes in Oregon, USA, to predict the timing and magnitude of hydrologic response at multiple soil depths for 36-hr intervals. We find that observation records as short as 6 months are sufficient for accurate predictions, and our model captures hydrologic response for high-intensity rainfall events even when those storm types are excluded from model training. We conclude that machine learning can provide an accurate and computationally efficient alternative to empirical methods or physical modeling for landslide hazard warning.

**Plain Language Summary** Rainfall-triggered landsliding is widespread, damaging, and deadly. These landslides are also difficult to predict and require complex models to completely assess the risk of a single area. This is a time- and resource-intensive process that makes it difficult to easily integrate into a system designed to give residents early warning of a potential landslide in their community. In an effort to work around these limitations, we introduce an alternative model based on artificial intelligence, which only requires a few minutes to develop and relies on easy-to-record information such as rainfall and soil moisture. We find this new model accurately forecasts essential information for establishing landslide risk and does so in significantly less time than similarly performing models. Therefore, when presented with the need to help inform community decision making, we encourage this type of modeling, given it takes little time to develop and produces accurate predictions of essential information for assessing community risk.

## 1. Introduction

Rainfall-induced shallow landslides pose a threat to communities situated in mountainous terrain. These natural hazards are deadly and can incur up to \$500 million (USD, 2020 adjusted) in economic losses from a single event (Turner & Schuster, 1996). Furthermore, there are over 294,000 individual landslides identified in the conterminous United States, with additional mapping still needed to complete a nationwide inventory (Mirus et al., 2020). Assessing the potential for landslide initiation is a crucial step for developing an early warning system for at-risk communities and relies on predictions of hillslope response to rainfall. This is often facilitated by hydrologic models characterized by varying degrees of complexity, such as empirical thresholds that relate rainfall and/or soil moisture measurements that correspond to past landslide events (e.g., Guzzetti et al., 2008; Mirus et al., 2018; Wiczorek & Guzzetti, 2000), or deterministic, physically based numerical models (e.g., Bellugi et al., 2015; Montgomery & Dietrich, 1994; Simunek et al., 2005). There are unique advantages to each method: empirical relationships between soil moisture, rainfall, and landsliding provide an efficient, regional-scale means of characterizing landslide initiation potential but have limited predictive accuracy (Bogaard & Greco, 2018; van Natijne et al., 2020). On the other hand, hydrologic modeling of saturated and unsaturated flow can be used to develop thresholds for assessing distributed landslide potential and can be extended beyond the observed record (e.g., Fusco et al., 2019; Thomas, Mirus, & Collins, 2018) instead of relying solely on statistical analyses. Hydrologic modeling of subsurface flow is relevant for hazard assessment, as it provides quantitative estimates of pore pressures in soils, which can be used to approximate the corresponding reduction of resisting stresses on hillslopes that can lead to slope failure

(Lu & Godt, 2008; Lu & Likos, 2004; Thomas et al., 2018). That said, models of variably saturated hydraulic and mechanical hillslope processes require significant effort to parameterize and validate, and the computational burden associated with their solution can limit their utility for operational (real time) warning systems. Further complications include the natural heterogeneity of soil structure, such as the presence of tree roots which add quantifiable tensile strength (Roering et al., 2003), and macropores that provide preferred channels of non-Darcy flow (McDonnell, 1990). Consequently, physical based modeling may not necessarily capture all the underlying physical processes in natural field settings.

To better constrain hydrologic response to rainfall, we propose an alternative method based on deep learning (DL)—an approach that requires less physical parameterization and trains faster than existing multidimensional flow models. DL-based approaches have already shown significant promise in the field of hydrology (Shen et al., 2018), and here we propose the use of specific DL-based algorithms that can learn and forecast hydrologic conditions from time series. This method relies on the quality and abundance of in situ soil moisture or pore-pressure measurements to provide an empirically derived, site-specific hydrologic data set which implicitly captures the characteristics of multidimensional variably saturated flow. We base our DL application on three unique requirements that are essential considerations for integrating a DL model with an early warning system: (1) evaluating how well a calibrated model can perform on unseen data (i.e., general model performance), (2) finding a critical length of input data for sufficient model performance (i.e., setting minimum performance requirements), and (3) how well a model can predict conditions associated with high-intensity rainfall when the observation data used for model training does not include high-intensity events (i.e., model extrapolation capability).

Here we develop an explicit, data-driven analysis of these requirements for successful early warning system integration and demonstrate the utility of DL for accurately modeling 3-D variably saturated flow from data representative of typical early warning systems. We further show how DL algorithms provide accurate forecasts of pore pressure response up to 36 hr in advance—a relevant timescale for landslide risk mitigation. While we do not suggest that DL can replace the insights gained from physically based models, it is a promising method for forecasting soil hydrologic response in highly heterogeneous or otherwise complex landscapes where comprehensive physical modeling would be computationally prohibitive.

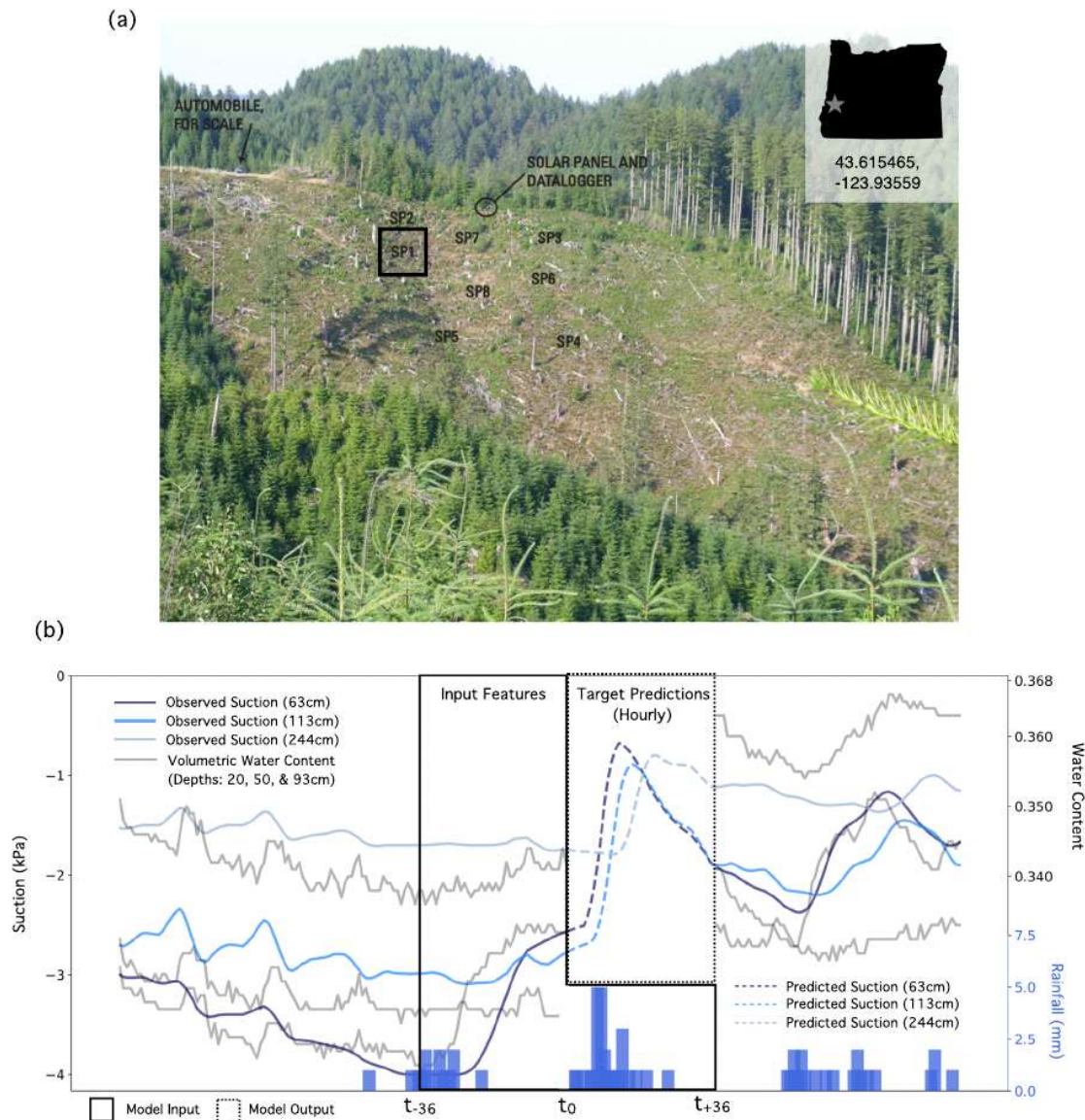
## 2. Methods

### 2.1. Data Source

We used data collected from the Knife Ridge monitoring site in the Elliot State Forest, Oregon, USA (Smith et al., 2014) (Figure 1a). The Oregon Coast Range is characterized by steep, soil-mantled hillslopes that are prone to shallow landslides that transition into debris flows, such as those triggered by historic storms in 1964 and 1996 (Coe et al., 2011; Montgomery et al., 2009; Robison et al., 1999; Wiley, 2000). Previous studies have shown that hydrologic response in this landscape is challenging to model as a result of strong hydrologic connectivity between the heterogeneous soil mantle and shallow zones of fractured bedrock (Ebel et al., 2007, 2008; Mirus et al., 2016). The monitoring site is located within a valley axis with an upslope contributing area of approximately 300 m<sup>2</sup> and features greater than 30° slopes with an average soil depth between 0.9 and 2.1 m (Smith et al., 2014). The instrumental record includes hourly measurements of rainfall, as well as soil moisture and pore pressure (suction) at three depths acquired from 2009 to 2012 (Smith et al., 2014) and has been the subject of prior 3-D physically based modeling efforts (Mirus et al., 2016).

### 2.2. Machine Learning Methods

Artificial Neural Networks (ANNs) have broad application to classification and regression-based problem solving, owing to their ability to approximate a wealth of mathematical relationships between input and output variables (Hornik et al., 1989). ANNs are already utilized in geoscience applications (e.g., DeVries et al., 2017) and have been used to model highly nonlinear processes common in hydrology (Abraham & See, 2007). Other uses of neural networks or machine learning (ML) in hydrology include time-dependent ANNs capable of filling data gaps in hydrologic times series (Ren et al., 2019), as well as tree-based machine learning algorithms for estimating soil-hydrologic parameters from physical or textural soil properties (Araya & Ghezzehei, 2019).



**Figure 1.** (a) Oblique view of the Knife Ridge monitoring site featuring all instrumented soil pits (SPs), including the pit for which we model pore pressures (black box). As the site sits on a slope  $>30^\circ$  located within a convergent valley axis, variably saturated flow takes place both laterally and vertically. Adapted from Smith et al. (2014). (b) Conceptual diagram showing model inputs and outputs. During training, a moving window slides across the input data provided to it (solid), and the model adjusts its parameters to produce a sequence of pore pressure values (dashed) from the model inputs that best matches the observed pore pressure sequence for those timesteps (not pictured). This process repeats until the model converges on a set of a parameters that produces the lowest mean squared error measured across all predicted and observed sequences.

Specifically, ANNs consist of one or more hidden layers of neurons that each contain a set of weights that are applied across input variables, plus an added bias. The weighted sum of a neuron is subsequently non-linearized by an activation function. Hidden layers of neurons connect input and output variables. The various combinations of weights and biases across all neurons are then trained by changing their values such that they minimize a fixed error metric like the root-mean-square error (RMSE) or mean absolute error to provide the proper nonlinear transformation of input variables to a corresponding output variable or variables.



A variation of traditional ANNs is the Recurrent Neural Network (RNN), which is well suited for processing sequential or temporal data, given a RNN's ability to incorporate information from the previous timestep and make predictions for the next timestep(s) based on weighting past and present inputs. A popular variant on the traditional RNN cell is the long short-term memory (LSTM) cell (Hochreiter & Schmidhuber, 1997). By design, a LSTM cell contains an internal state which acts as its memory and is iteratively adjusted and propagated through time. The internal state allows the cell to handle longer term temporal dependencies that traditional RNN cells are not able to explicitly incorporate within their architecture. Furthermore, LSTM-based neural networks are conceptually better suited than statistically based autoregressive time series models, given a LSTM's capacity to approximate nonlinear relationships between input and output variables, as opposed to assuming linear relationships between lagged endogenous or exogenous variables in most autoregressive models (Box et al., 2008). This is particularly relevant for the nonlinear physical processes that govern variably saturated subsurface flow (Richards, 1931). For a more in depth discussion of LSTM cells, we refer to Olah (2015), and for applications to hydrology, we refer to Kratzert et al. (2018).

We use an LSTM-based “encoder-decoder” model with a global Luong attention mechanism (Luong & Pham, 2015)—an architecture we chose through an extensive trial and error-based process considering computational processing time, ease of use, and consistency of results. The encoder-decoder architecture consists of two parts: an “encoder” that reads in and learns an input sequence and a “decoder” that receives a fixed representation (understanding) of the input sequence from the encoder and learns the proper nonlinear transformations to translate the input to an output sequence of variable length (Sutskever et al., 2014). For temporal data, the encoder learns the functional relationships of the input sequence, and the decoder learns the necessary transformations to translate the previous input sequence to a sequence of predicted values. The decoder does so one step at a time based on the input sequence itself, as well as the previous timestep of the prediction sequence.

Our model consists of 24 unidirectional LSTM units in both the encoder and decoder, which feed to a layer of 75 connected neurons with a 50% dropout regularization rate for further processing, and finally connect to a layer of three neurons outputting a vector of 36 hourly predictions at each of the three tensiometer depths. We script our model in the Python programming language, utilizing the Keras frontend API (<https://keras.io/>) with a Tensorflow backend (<https://www.tensorflow.org/>) and the Adam optimizer (Kingma & Ba, 2014). We use Scikit-learn (Pedregosa et al., 2011) for data preprocessing and postprocessing. As model weights are set randomly upon initialization, each model run typically converges on a similar but not necessarily identical solution. However, training for 2,000–5,000 epochs consistently results in a series of weights and biases that lead to comparable results across model runs. Typical training time takes between 2–10 min on a single graphics processing unit (GPU) in the Google Collaboratory scripting environment ([colab.research.google.com](https://colab.research.google.com)).

### 2.3. Data Preprocessing and Experimental Framework

Modeling steps include preparing input sequences of the previous 36 hr of data at 1-hr resolution from all sensors (rainfall, soil moisture, and tensiometer) and the measured maximum and cumulative rainfall for the next 36-hr interval. We represent this future 36-hr rainfall input (herein referred to as a *forecast*) through 18 2-hr intervals of max and cumulative rainfall data. These input data pair with the corresponding pore pressure data within the prediction interval at each tensiometer depth and frame our study as supervised learning regression problem. In doing so, we provide our model with both prior and anticipated hydrologic information as inputs and seek to draw an explicit link between these inputs and the corresponding pore pressure response within the 36-hr rainfall forecast period (Figure 1b). Model training then occurs by finding the best set of nonlinearized weights and biases that apply to current and past information which most closely match the observed pore pressure response. For this implementation, we choose the recorded rainfall data as forecasted information because it allows our algorithm to approximate the functional relationships between soil moisture response and rainfall. As such, we do not incorporate uncertainty into rainfall forecasts in this contribution.

To assess the efficacy of our LSTM-based model, we explicitly address the three requirements necessary for application in early warning systems. Specifically, we ask the following questions: (1) Given a model trained on 2 years of data, how well can it forecast pore pressure for the following year? (2) To what extent does the

length of the training data set affect our ability to make accurate predictions?; and (3) if our training data set does not include high intensity events, how well can we predict pore pressure for high intensity rainfall outside of the model's calibrated range? For this exclusion process, we omit rainfall events with intensities  $>4$  mm/hr across all water years—a relatively low intensity value that corresponds to the mean hourly intensities of two 1996 storms that caused mass wasting across the Oregon Coast Range. The first question demonstrates the algorithm's ability to learn from a variety of soil moisture response examples and tests anticipated general performance; the second question tests how much information our model needs to provide accurate forecasts, thus establishing a minimum requirement for available training data, and finally, the third question tests our algorithm's ability to extrapolate response governed by highly nonlinear processes and potentially predict response to extreme, never-recorded events.

### 3. Results

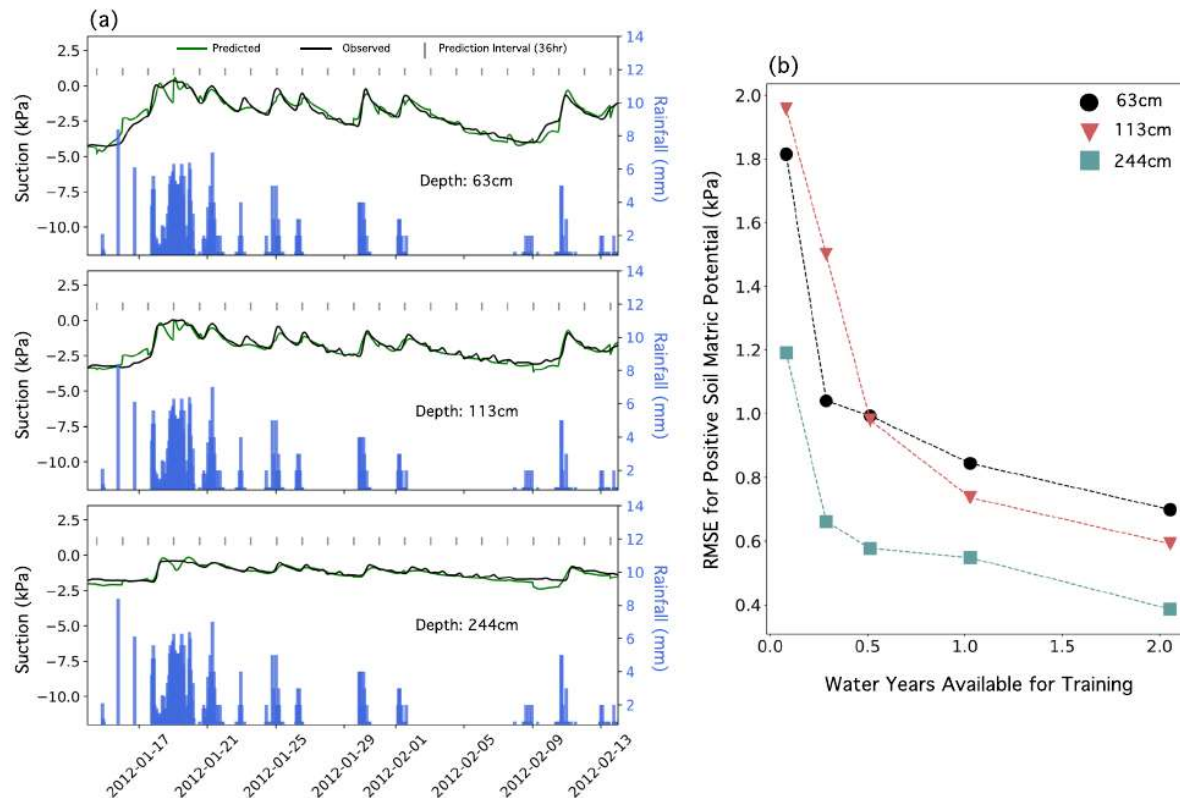
Our results demonstrate that the LSTM-based model can yield highly accurate predictions ( $RMSE < 1$  kPa for positive pore pressures) for Water Year 3 (1 October 2011–31 September 2012) in as little as 2 min (computational time) of training on Water Years 1 and 2 using a single GPU processor, thus addressing our model's general performance capacity. As an example, Figure 2a shows predictions for pore pressure (suction) at 36-hr intervals from 14 January to 14 February 2012 (a subsection of Year 3) at all tensiometer depths. This 1-month illustration includes many 36-hr prediction intervals that show a rise and decay of pore pressure in response to rainfall events. While 36-hr prediction intervals generally agree with the corresponding observed intervals, our model sometimes fails to predict periods of wetting or drying during intervals that feature continuous rainfall over several days. For instance, in the long sequence of rainfall events between 17 and 21 January, our model incorrectly predicts drying conditions with a decrease in pore pressure. Nonetheless, these types of errors are infrequent and unrepresentative of general model performance, as the correlation coefficients between observed and simulated values exceed 0.96 (Figure S1 in the supporting information).

To establish minimum performance requirements, we progressively resampled our training data set into shorter and shorter subsets and then tested its performance for the third year of our record. Figure 2b shows the drop in model performance is most prominent when we reduce sampling to less than 6 months of observations, which we posit as a minimum sampling threshold for the data set. While this number will vary based on the data set provided, having a baseline value for training data provides valuable insight for similar endeavors at other field sites and demonstrates an important minimum observation requirement for accurate predictions.

Finally, to demonstrate model extrapolation capacity, Figure 3a shows 36-hr predictions for intervals with rainfall intensities above the 4 mm/hr training threshold. Overall, our intensity-limited model demonstrates reasonable accuracy in estimating rising, peak, and falling limbs of individual prediction intervals but shows infrequent areas of high inaccuracy, particularly for prolonged periods of rainfall over the 4 mm/hr threshold. Figure 3b shows absolute prediction error between our original and intensity-limited models at each tensiometer depth. While the intensity-limited model features the largest error values, overall error approximates the mean error values of our original model, both of which lie within or near the  $\pm 0.5$  kPa margin of instrumental tensiometer error (Smith et al., 2014). Thus, even constraining the model training to nonanomalous rainfall events still allows for accurate—if not always consistent—predictions in response to higher intensity rainfall events.

### 4. Discussion

The heterogeneity of landslide-prone hillslopes poses challenges to the processes encoded in hydrologic models. For example, complicating factors such as tree roots, macropores, and soil horizons, and otherwise, heterogeneous soil conditions limit the ability for a simple, single parametrization to properly characterize field conditions. Mirus et al. (2016) simulate pore pressure values on Knife Ridge through 3-D numerical subsurface flow modeling. Their model parameterization includes topographic data, soil depth information, and five hydraulic property parameters for each of the three hydrogeologic units included in their study. As a result, their work provides an important physical analog and gives valuable insight into the controls of hydrologic response, but does not reach the same level of accuracy with pore pressure predictions in comparison to our DL model. An increase in the number of modeling scenarios such as those

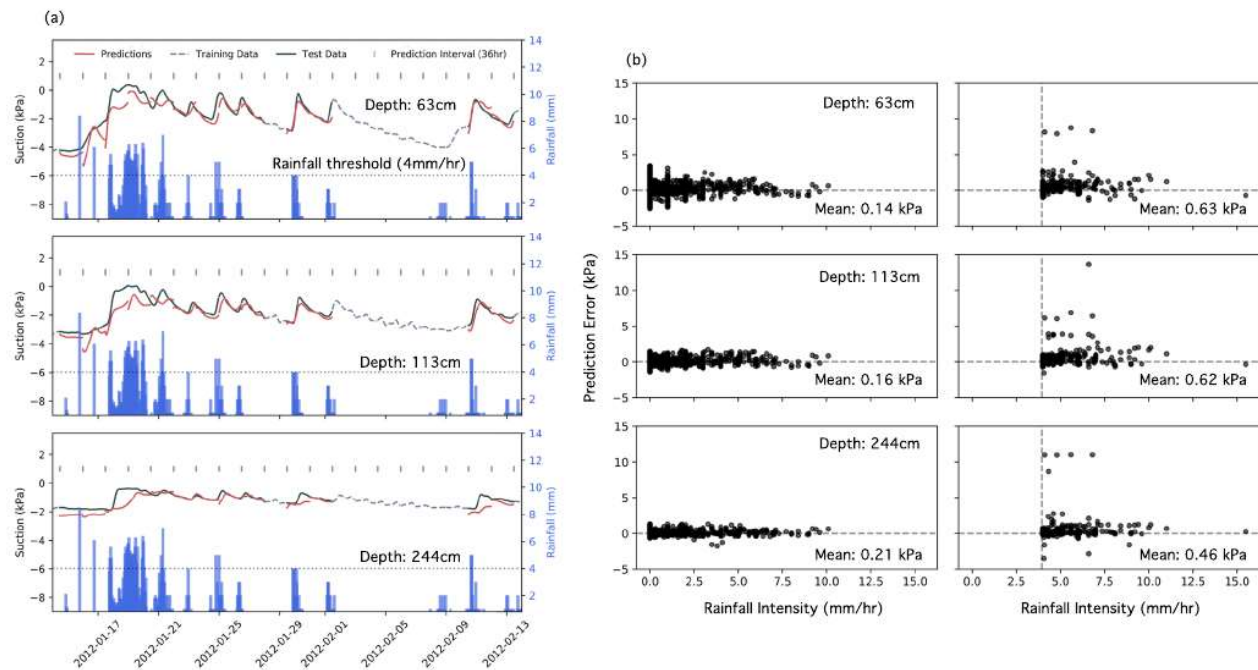


**Figure 2.** (a) Predicted and observed pore pressure response from 14 January to 14 February 2012, delineated by each 36-hr prediction interval. (b) RMSE of positive pore pressure predictions as a function of available training data. Data subsampling occurred by randomly selecting training samples and their corresponding targets without replacement from a total population of training data from Water Years 1 and 2. This introduces possible random sampling error but eliminates any bias from choosing only samples from dry or wet months. With a limited number of training samples, however, we suggest selecting data that most closely approximates the intended conditions one chooses to model.

utilized by Thomas, Mirus, and Collins (2018) can begin to account for inaccuracies behind a single physical model parameterization, yet the extended processing time even for 1-D infiltration scenarios is problematic, and this limitation will only increase with additional dimensions. The ML-based modeling presented here outperforms the processing time of the HYDRUS-1D (Simunek et al., 2005) model utilized by Thomas, Mirus, and Collins (2018) by as many as three orders of magnitude (128 hr vs. 2–10 min). Thus, with the natural heterogeneity and uncertainty of soil conditions for field sites, a well calibrated ML-based model has the capability to learn and account for site-specific characteristics without imposing a computational limitation.

As our sensitivity tests demonstrate, the limits of our model's accuracy are determined by the quantity and quality of the training data, which as a prerequisite must capture the underlying physical relationships we seek to model. Because our study area is characterized by a Mediterranean climate, training data are required during fall and winter months when rainfall events that promote landslides are most common. Furthermore, our results suggest that if training data happen to be acquired during a period lacking rainfall events of significant intensity, the model can approximate soil hydrologic response to high rainfall events, albeit with reduced accuracy. This issue of extrapolation beyond conditions within the period of record is common to many environmental and hazards research pursuits.

By closely approximating the timing and magnitude of rises in pore pressure along a variety of wetting/drying conditions, our LSTM-based model demonstrates a fast, accurate, and computationally efficient alternative to physically based modeling of landslide hazard. We anticipate that this approach can provide accurate predictions for integration into landslide early warning systems. Our results suggest that it is



**Figure 3.** (a) Intensity-limited pore pressure response from 14 January to 14 February 2012. (b) Comparison of error values based on rainfall intensity. Model absolute error on testing data after training on all rainfall intensities featured in Water Years 1 and 2 (left). Intensity limited model absolute error from all rainfall intensities at or above 4 mm/hr across all water years (right).

possible to train an algorithm that does not require the same sets of parameters as physical models but uses site-specific data to capture the complexity of in situ measurements and replicates the physical relationships behind 3-D flow for variably saturated subsurface conditions.

We present our model as a proof-of-concept for how machine learning can help forecast conditions for use in early warning systems. Several modifications could generate improved results, such as an increase in the length of observation data, the potential for additional insight from multihead convolutional layers such as those utilized by Zheng et al. (2014), or adapting more advanced attention-based models such as the Transformer (Vaswani et al., 2017). The latter represents a promising next step. As the physical significance of a neural network's weights are challenging to interpret, a more in-depth study of attention in future network architectures may provide further insight into the influence of each physical input at each timestep.

## 5. Conclusions

We demonstrate how an LSTM-based DL algorithm can accurately predict the timing and magnitude of pore pressure response to rainfall in 36-hr intervals. Our model is computationally efficient and can be used to provide real-time forecasts of hydrologic response conditions on landslide-prone hillslopes for early warning. The quantity and quality of the training data used for the model serve as a first-order limit on the model's predictive capability. We further show that when trained on exclusively low intensity rainfall, our model can approximate pore pressure response to high intensity events. With previous work exemplifying the mathematical capabilities of ANNs to learn and understand physical processes in hydrology and geosciences, we present this model as a next step to more accurately constrain near-surface hydrologic response in naturally heterogeneous areas where physically based modeling is computationally prohibitive.

## Data Availability Statement

Machine learning code is available at <https://github.com/eorland> website. Knife Ridge hydrologic data are available at <https://pubs.usgs.gov/of/2013/1283/> website. Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.



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