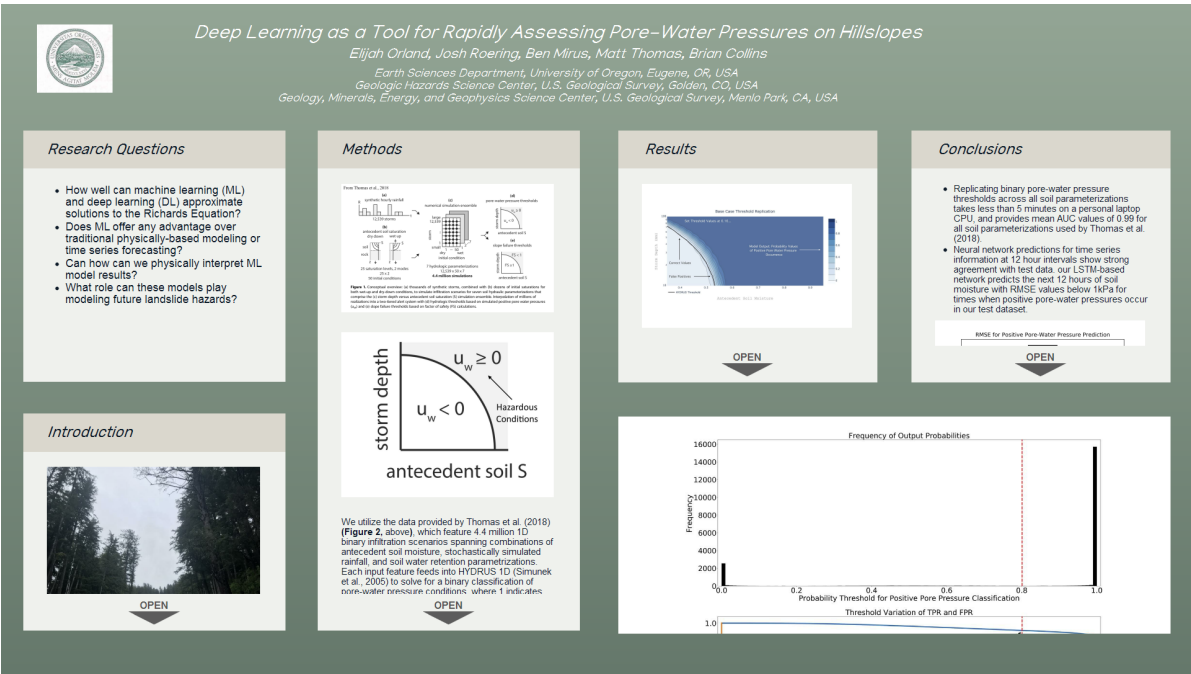


Deep Learning as a Tool for Rapidly Assessing Pore-Water Pressures on Hillslopes



Elijah Orland, Josh Roering, Ben Mirus, Matt Thomas, Brian Collins

Earth Sciences Department, University of Oregon, Eugene, OR, USA
Geologic Hazards Science Center, U.S. Geological Survey, Golden, CO, USA
Geology, Minerals, Energy, and Geophysics Science Center, U.S. Geological Survey, Menlo Park, CA, USA

PRESENTED AT:



RESEARCH QUESTIONS

- How well can machine learning (ML) and deep learning (DL) approximate solutions to the Richards Equation?
- Does ML offer any advantage over traditional physically-based modeling or time series forecasting?
- Can how can we physically interpret ML model results?
- What role can these models play modeling future landslide hazards?

INTRODUCTION



- Precipitation induced shallow landsliding poses a common and continual threat to communities situated below steep hillslopes, such as the 2015 Kramer Ave debris flow

in Stika, AK (**Figure 1**, above)

- Predicting a landslide event relies on an understanding of pore-water pressure response to rainfall, which is deterministically quantified by the Richards Equation (Van Genuchten, 1980)
- Deep Learning provides an approach for pore-water pressure modeling—a highly non-linear process. It can learn the Richards Equation and provides solutions faster than traditional modeling software, as well as forecast a series of hourly pore-water pressures from time series.
- We show the potential for deep learning for approximating solutions to the Richards Equation, and how deep learning models for time series can forecast pore-water pressure response to rainfall across time.

METHODS

From Thomas et al., 2018

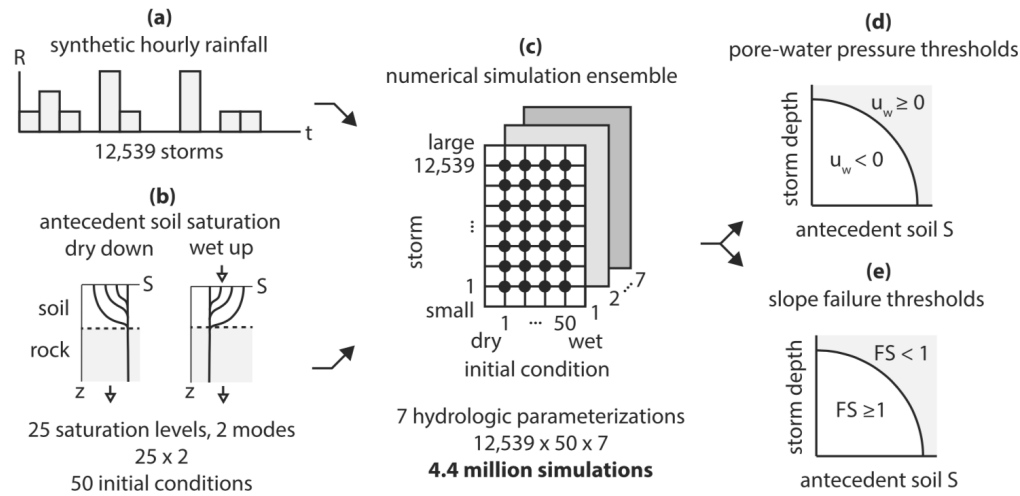
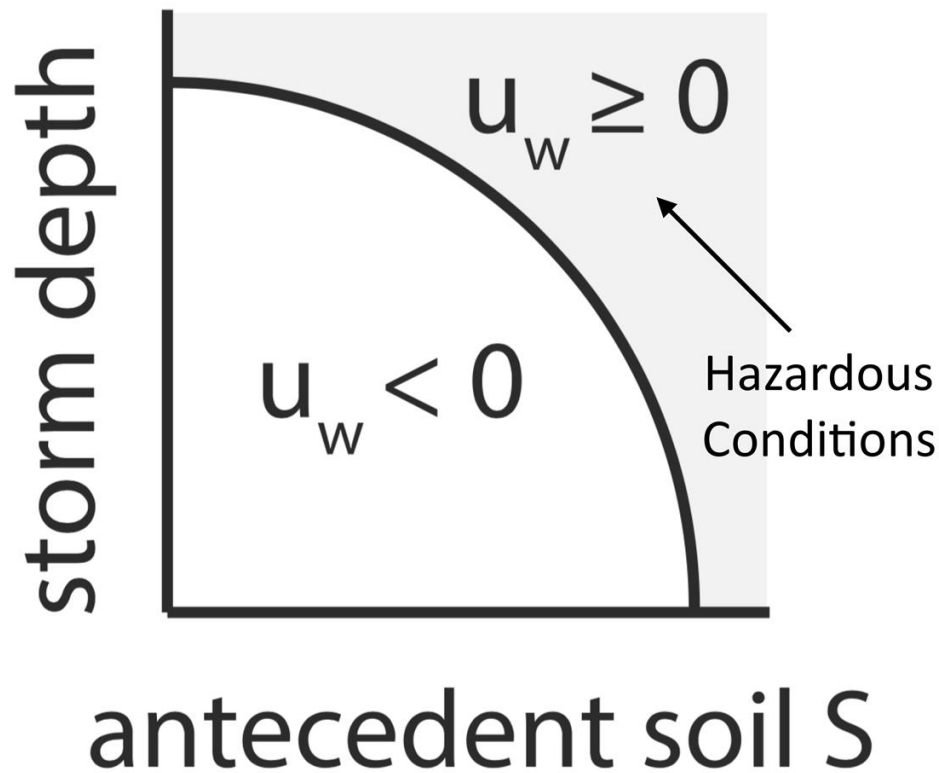
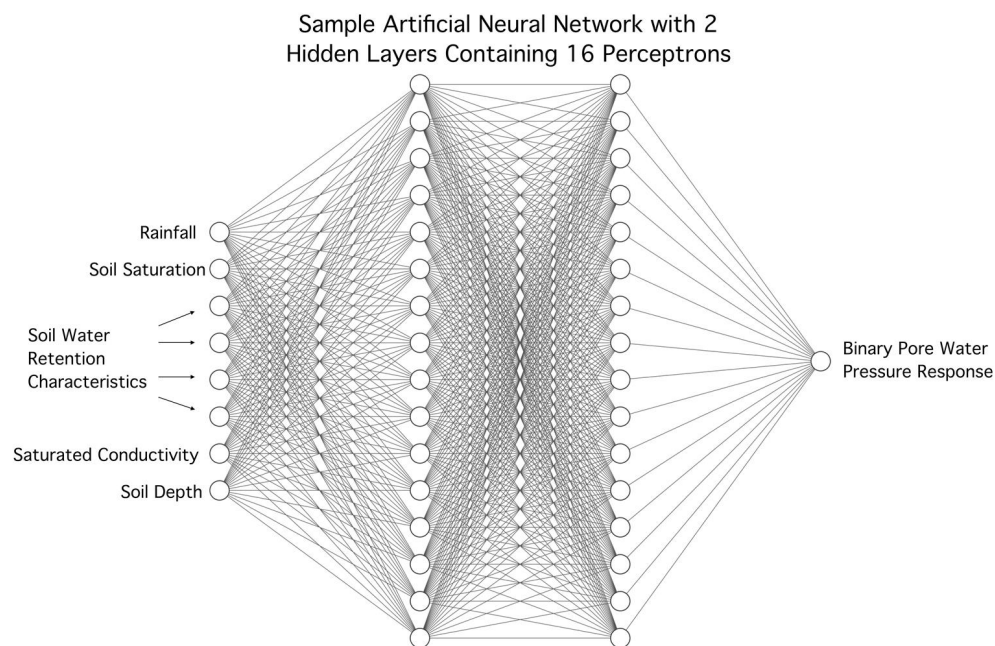


Figure 1. Conceptual overview: (a) thousands of synthetic storms, combined with (b) dozens of initial saturations for both wet-up and dry-down conditions, to simulate infiltration scenarios for seven soil hydraulic parameterizations that comprise the (c) storm depth versus antecedent soil saturation (S) simulation ensemble. Interpolation of millions of realizations into a two-tiered alert system with (d) hydrologic thresholds based on simulated positive pore water pressures (u_w) and (e) slope failure thresholds based on factor of safety (FS) calculations.

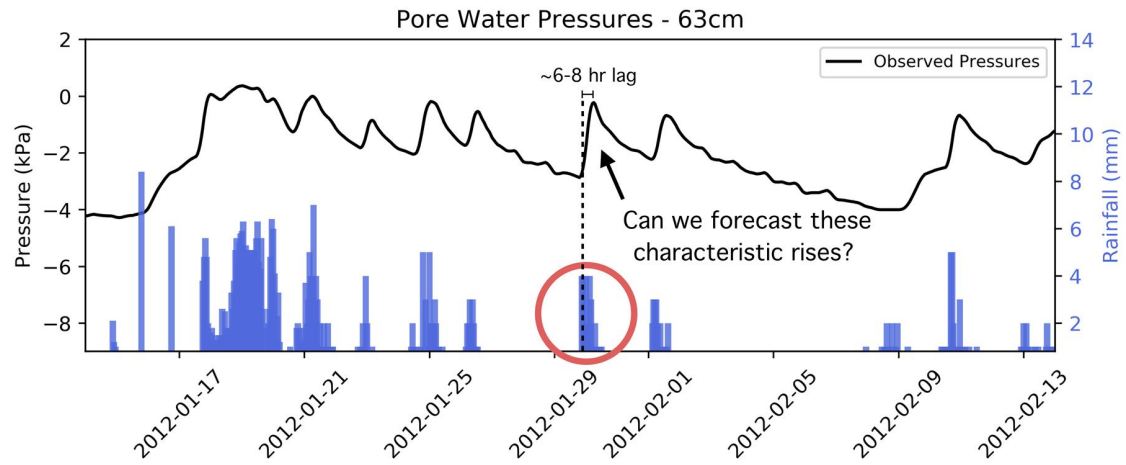


We utilize the data provided by Thomas et al. (2018) (**Figure 2**, above), which feature 4.4 million 1D binary infiltration scenarios spanning combinations of antecedent soil moisture, stochastically simulated rainfall, and soil water retention parametrizations. Each input feature feeds into HYDRUS 1D (Simunek et al., 2005) to solve for a binary classification of pore-water pressure conditions, where 1 indicates positive pore-water pressures, and 0 indicates a value below the positive threshold.

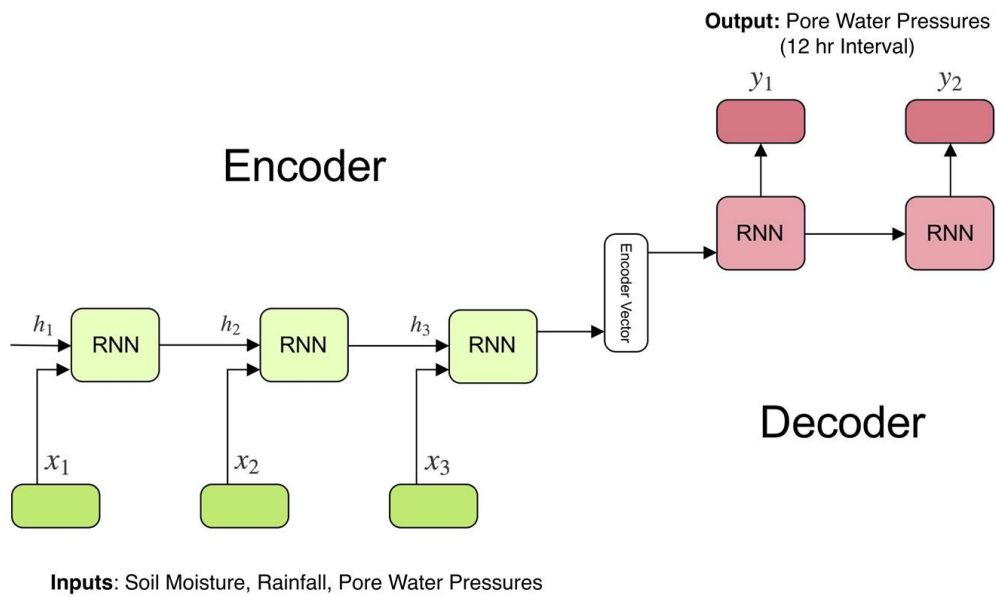


To replicate thresholds in the binary dataset, we employ a feed-forward multi-layer perceptron (MLP) model architecture (**Figure 3**, above). Our most successful model utilizes two hidden layers, each with 64 perceptrons activated by the softmax function, and a single output perceptron with sigmoid activation.

We also apply a Long Short Term Memory (LSTM) model architectures to a time series of rainfall, soil moisture, and pore-water pressures from Elliot State Forest in the Southern Oregon Coast Range (Smith et al., 2013). We hypothesize that an LSTM-based neural network is capable of learning the Richards Equation implicitly from time series information, and can predict rises in pore-water pressures accordingly (**Figure 4**, below).



We utilize a model with two LSTM layers each with 32 units formatted in an encoder-decoder-style (**Figure 5**, below), with the cell state of the encoder carried across all batches of input data. This method is traditionally referred to as “sequence-to-sequence” (seq2seq) modeling.



<https://towardsdatascience.com/understanding-encoder-decoder-sequence-to-sequence-model-679e04a4346>

RESULTS

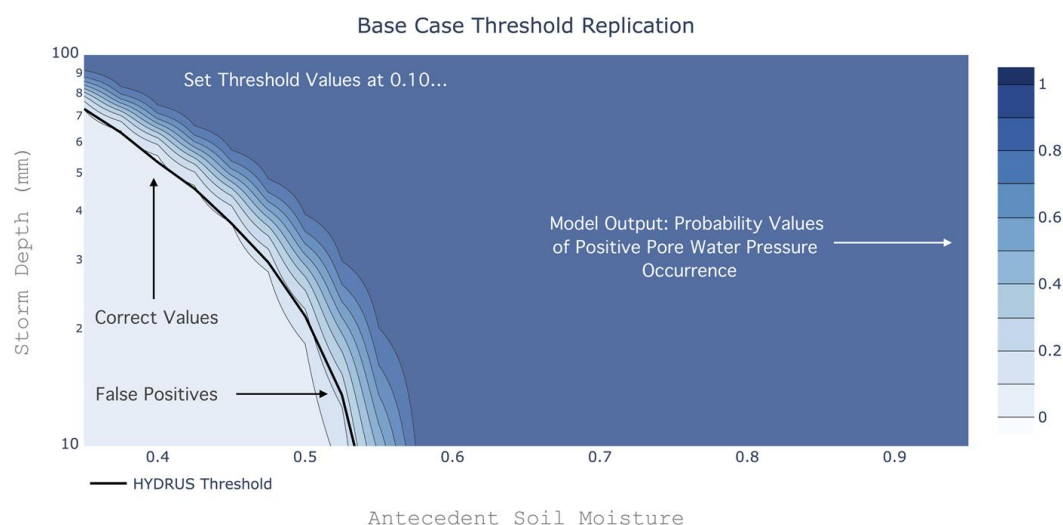
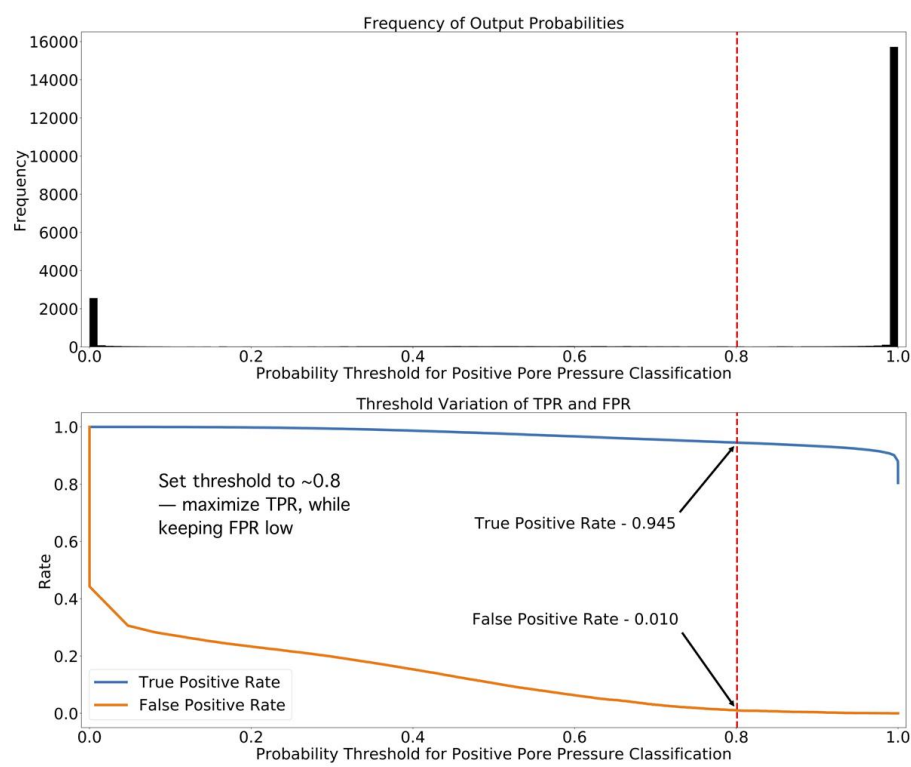
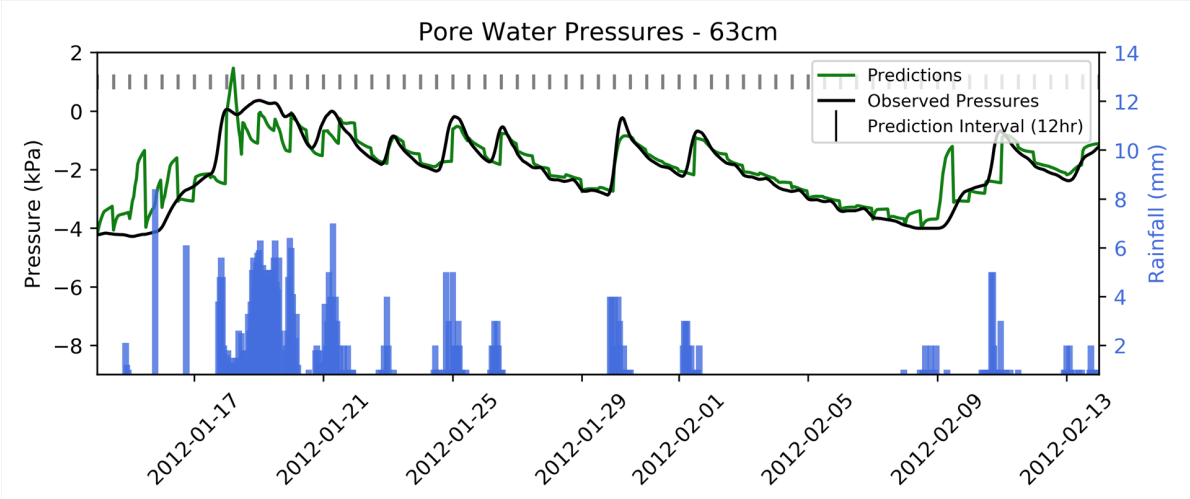


Figure 6 (above) demonstrates the ability for ANNs to recreate binary pore water pressure thresholds. The solid black line represents the threshold from Thomas et al. (2018), while lighter lines represent isolines of probability that a positive pore-water pressure occurred. Isoline values range between 0 and 1, where 1 indicates absolute certainty of the occurrence of a positive pore-water pressure. For the Base-Case threshold in Figure 1, the physically determined threshold overlaps probability values of between ~0% and 20% certainty.

Figure 7 (below) shows a histogram of output probabilities and how the relationship between true and false positive rates varies as a function of setting a probability for threshold determination. For instance, setting a probability threshold of 0.8 (or 80% certainty) achieves close to a 95% true positive rate, while retaining a false positive rate near 0. The stratification of output probability values demonstrates the model output as either very confident ($0.8 <$) or not at all confident (<0.05) in pore-water pressures occurring. Thus, setting a threshold at 0.8 captures nearly all true positives without risk of false positives. This is not readily seen in a set of probability isolines as those shown in **Figure 6**.

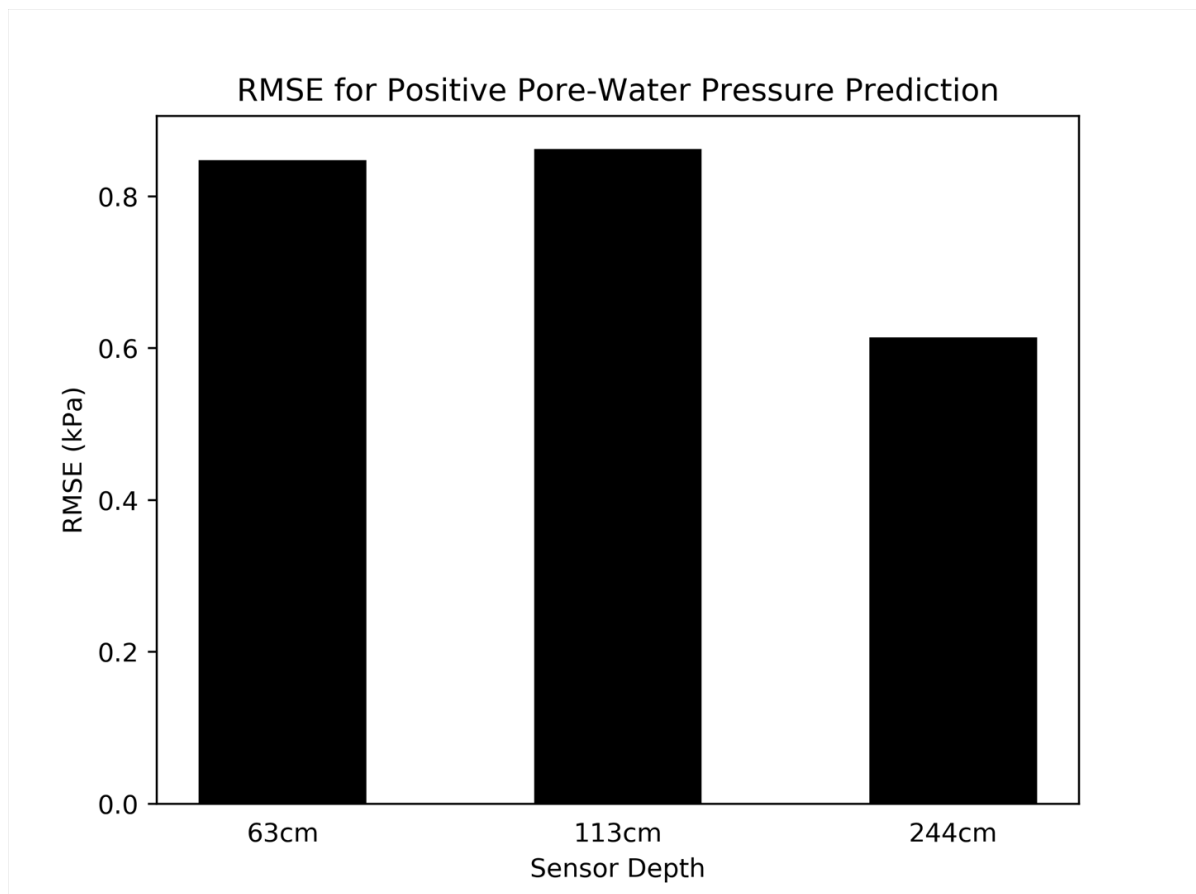


We present predictions from an LSTM-based neural network in **Figure 8** (below). Our model outputs predictions in 12 hour intervals, and demonstrates 'learned' relationships between antecedent soil moisture, rainfall, and pore-water pressure response, and demonstrates a strong relationship between observed pore-water pressure data and predicted values. Model error is below 1kPa for all values for which positive pore-water pressures occur (**Figure 9**, right)



CONCLUSIONS

- Replicating binary pore-water pressure thresholds across all soil parameterizations takes less than 5 minutes on a personal laptop CPU, and provides mean AUC values of 0.99 for all soil parameterizations used by Thomas et al. (2018).
- Neural network predictions for time series information at 12 hour intervals show strong agreement with test data. our LSTM-based network predicts the next 12 hours of soil moisture with RMSE values below 1kPa for times when positive pore-water pressures occur in our test dataset.



- We encourage these methods over other statistical techniques such as autoregressive models, given the highly-non linear nature of the Richards Equation.

CV

ELIJAH
ORLAND

615-423-4288
ELIORLAND@ATT.NET
EORLAND.ORG

EDUCATION

Masters of Science - Earth Science
University of Oregon / 2018-20

Research: Using machine learning for rapidly assessing hazardous conditions on hillslopes, coupled with in-the-moment pore-water pressure predictions from time series using deep recurrent neural networks.

Bachelors of Arts - Geology with Spanish Minor
Middlebury College / 2014-18
Magna Cum Laude

Thesis: Using remote sensing and high-resolution digital elevation models to identify potential erosional hotspots along river channels during high discharge events.

EXPERIENCE

Graduate Student Researcher
University of Oregon / 2018-20

Part of a NSF-funded, interdisciplinary project to install a landslide early warning system using state-of-the-art analytical techniques and ample community involvement. Led by Nobel Laureate, Robert Lempert, of the RAND Corporation, with direction by Dr. Josh Roering of the University of Oregon. Publication in prep: Machine Learning Applications for Landslide Hydrology

Graduate Teaching Fellow
University of Oregon / 2018-20

Lab Instructor for multiple classes in Geology and Geography; recognized as an engaging and effective instructor by professors and students.

SOFT SKILLS

Communication - Advanced

Problem Solving - Advanced

Data Cleaning - Proficient

Research and Synthesis - Proficient

PROFILE

I'm an Earth Scientist who specializes in the quantitative analysis of geospatial data. My current research utilizes machine learning and predictive modeling within the Geosciences to understand and assess landslide hazard. I am fascinated with deep learning, and focus on multistep time series forecasting.

Always learning.

TECHNICAL SKILLS

Python

Proficient

R / MATLAB

Intermediate

Machine Learning

Proficient

ArcGIS

Advanced

REFERENCES

Dr. Josh Roering
Department Chair - Earth Science
541-346-5574
jroering@uoregon.edu

Dr. Annette Patton
Postdoctoral Researcher
541-231-8937
annetep@uoregon.edu

Dr. Matthew Thomas
Research Hydrologist
650-678-0375
matthewthomas@usgs.gov

16 of 19

1/16/20, 8:37 PM

ABSTRACT

We apply deep learning to a synthetic near-surface hydrological response dataset of 4.4 million infiltration scenarios to determine conditions for the onset of positive pore-water pressures. This provides a rapid assessment of hydrologic conditions of potentially hazardous hillslopes where mass wasting is prevalent, and sidesteps the computationally expensive process of solving complex, highly non-linear equations. Each scenario considers antecedent soil moisture and storm depth with varying soil properties based on those measured at a USGS site in the East Bay Hills, CA, USA. Our model combines antecedent soil wetness and storm conditions with soil-hydraulic properties and predicts a binary output of whether or not positive pore pressures were generated. After parameterization, pore-water pressure conditions can be returned for any combination of antecedent soil moisture content and storm depth values. Similar to previous work, a deep learning model reduces computational cost: processing time is decreased by more than an order of magnitude for 1D simulated infiltration scenarios while maintaining high levels of accuracy. While the physical relevance and utility behind process-based numerical modeling cannot be replaced, the comparatively reduced computational cost of deep learning allows for rapid modeling of pore-water pressure conditions where solving complex, highly non-linear equations would otherwise be required. Furthermore, comparing the solution of a deep learning model with a hydrological model exemplifies how similar results can be produced through highly divergent mathematical relationships. This provides a unique opportunity to understand which variables are most relevant for the prediction of positive pore-water pressures on hillslopes, and can represent landslide-relevant hydrologic conditions for hillslopes where rapid analysis is imperative for informing potential hazard mitigation efforts. Ultimately, a calibrated deep learning model may reduce the need for computationally expensive physics-based modeling, which are often time and resource intensive, while providing critical statistical insight for the onset of hazardous conditions in landslide-prone areas.

REFERENCES

Simunek, J., Genuchten, M. Van, & Sejna, M. (2005). The HYDRUS-1D software package for simulating the one-dimensional movement of water, heat, and multiple solutes in variably-saturated media. HYDRUS Software Ser.

Smith, B. J. B., Godt, J. W., Baum, R. L., Coe, J. A., Burns, W. J., Lu, N., ... Jewell, S. (2013). Hydrologic Monitoring of a Landslide-Prone Hillslope in the Elliott State Forest , Southern Coast Range , Oregon , 2009 – 2012. U.S. Geological Survey Open-file Report 2013-1283. Retrieved from <https://pubs.usgs.gov/of/2013/1283/pdf/of13-1283.pdf>

Thomas, M. A., Mirus, B. B., & Collins, B. D. (2018). Identifying Physics-Based Thresholds for Rainfall-Induced Landsliding. *Geophysical Research Letters*, 45(18), 9651–9661. <https://doi.org/10.1029/2018GL079662>

van Genuchten, M. T. (1980). A Closed-form Equation for Predicting the Hydraulic Conductivity of Unsaturated Soils1. *Soil Science Society of America Journal*. <https://doi.org/10.2136/sssaj1980.03615995004400050002x>

