A Physicist's Approach to the Water Cycle: Long-Term Changes in the Water Retention Properties of Soils in the Sevilleta Shrubland

William Crockett

Abstract—**New Mexico's environments are heavily dependent on the limited amount of water that they receive, and climate models predict further aridification of the Southwest. Although there have been studies on how climate change is changing precipitation patterns, less attention has been paid to modeling how climate change is impacting soil water content and hydraulic conductivity, which play a large role in determining water availability in ecosystems and agriculture. To analyze whether the soil moisture response to precipitation has changed, a 1-D model, Phydrus (https://github.com/phydrus/phydrus), was used to model soil water content in response to precipitation. Phydrus numerically solves the one-dimensional Richards Equation using the Van Genuchten-Mualem model to calculate the soil water content time series. We used a data set of half-hourly measured precipitation and soil moisture levels spanning 15 years from the SES station in the Sevilleta National Wildlife Refuge, collected by the Biology Department's Litvak Lab. The precipitation data was used as an input to model the soil water content. To look at changes in the response, we found the best parameters to fit the model to the soil moisture data for 1-month summer windows in 2008, 2013, and 2018. We show that while it takes similar parameter values to fit each window in the same year, the necessary parameters change between years. These parameters represent how water is absorbed into and conducted through the soil, and the changing values of saturated water conductivity and saturated water content suggest that the physical properties of the soil may be changing over the long-term. Differences in parameter values point to shifts in soil water response over the last 15 years, which means that the changes are occurring on a similar time-scale to climate change.**

I. Introduction

Over the next century, climate change will have profound effects on the planet. Studies have shown that the release of green-house gasses will lead to rising global temperatures, and an increased number of extreme weather events[1][2]. While the effect in local regions are harder to predict, models and data show that the Southwestern United States will have an increase in temperature and a change to its precipitation events [3]. Although models show a slight increase in total precipitation in the Chihuahuan desert, the events are predicted to become more extreme, leading to large rainfalls that lead to floods followed by long dry spells causing drought.

While many studies have been conducted to analyze and model the impact of climate change on Earth's atmosphere and oceans, much less attention has been payed to the impact of climate change on geology. Recently, an analysis of soil samples taken across the United states over the last 50 years shows a change in macroporosity over a time-scale comparable to climate change [4]. Macroporosity is a measure of the amount of soil composed of large macropores, which are responsible for a relatively high amount of water conductivity. In most climate models, geological properties are taken to be constant due to the assumption that they are changing much more slowly than the atmosphere. Showing that geological changes can occur on a similar time-scale illustrates the importance in understanding the impact of climate change on soil properties. If climate change is leading to change in macroporosity and other soil properties, it would impact water availability to ecosystems and agriculture.

To find long-term changes in soil properties, we analyzed a 15-year time-series of precipitation events and soil water content at the Sevilleta National Wildlife Refuge collected by the UNM Biology Litvak lab. The goal was to find a model that can accurately replicate the soil water content data at a given depth when the precipitation events were given as input. The best fit of the model to the data was found for different windows throughout

Advisor: Dr. Mousumi Roy, Department of Physics and Astronomy, University of New Mexico; with input from Dr. Marcy Litvak and Dr. Tomer Duman, Department of Biology, University of New Mexico

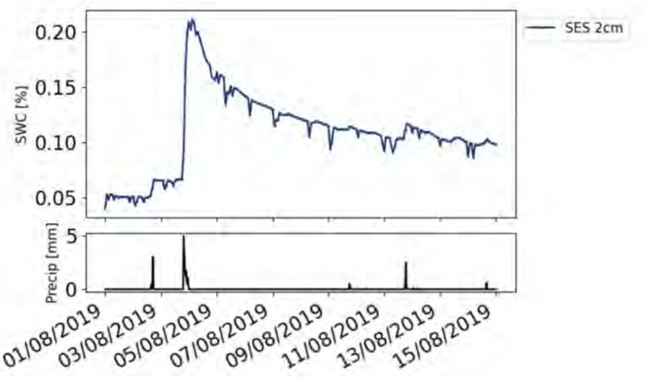

Fig. 1. A 15-day window of precipitation (bottom) and soil water content at a depth of 2 cm (top) at the US-SES site at the Sevilleta National Wildlife Refuge. The window is a good example of the similarity between the soil moisture response to a large precipitation event and an exponential decay function.

the time-series, and by comparing the parameter values of the best fit, we attempted to find patterns of changing soil properties.

By finding clear changes in the soil water response function over time, we can better understand how climate change is impacting the water cycle in New Mexico. The increase in macroporosity predicted by Hirmas et al. would mean lower saturated water conductivity, intensifying the water cycle [5]. For desert ecosystems, this would mean that when more extreme precipitation events occur, less of the water infiltrates the soil, leading to lower water availability [6]. Being able to properly model these changes will help us better understand the impacts of climate change in New Mexico, and allow the state to plan and prepare for the future.

II. Linear Model

We started the project by taking a zeroth order approach. The soil water content (SWC) following a precipitation event looks similar to an exponential decay, so we began by modeling SWC by the linear sum of the exponential decay functions that result from each precipitation event (figure 1).

The response function was modeled by:

$$g(t) = Ae^{\rho t} \tag{1}$$

We then used MATLAB to convolve the time-series of precipitation events $f(t)$ with the response function $g(t)$ to create a linear model of the SWC time-series $h(t)$. The convolution function is:

$$h(t) = (f * g)(t) := \int_{-\infty}^{\infty} f(\tau)g(t-\tau)d\tau \tag{2}$$

For a given window, a 3rd-degree polynomial was fit to the entire data window, and then subtracted from the data to reduce the effect of long-term changes in SWC on the model's fit. The Nelder-Mead algorithm was employed using MATLAB's fminsearch function to find the values of A and ρ that minimized the difference between the model and data to find the best fit [7]. An example of the output is shown in Figure 2.

As shown in the bottom plot of Figure 2, the linear model is able to approximate the response to a single precipitation event and represent the general response, but it failed to accurately simulate SWC for larger windows with more events. To analyze how the soil moisture response is changing, we needed a model that can accurately recreate the soil moisture time-series for a given set of precipitation events.

III. One Dimensional Physical Model

After our linear model failed to accurately model the data, we attempted to more accurately model the process by modeling the underlying physics of the system. An illustration of the system is shown in Figure 3. As shown, the system has a reliance between the water content and the water conductivity. As the soil dries out, paths for water to flow through shrink or are cut off, until the amount of water reaches a minimum, at which point water conductivity goes to zero.

A. The Richards Equation and the Van Genuchten-Mualem Model

We can model this relationship between water content and water conductivity using a differential equation. The infiltration of water into the soil is essentially a fluid flow through porous media problem, which is governed by the Richards Equation [8]. The equation represents the relationship between water content, pressure, and conductivity:

$$\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial z}\left[k(\theta)\left(\frac{\partial h}{\partial z} + 1\right)\right] \tag{3}$$

Where θ is the soil water content, t is time, z is depth, k is the water conductivity (how easily water can infiltrate the soil), and h is the pressure head. The dependence between the water content and water conductivity leads to non-trivial solutions to the equation, to some interesting nonlinear properties

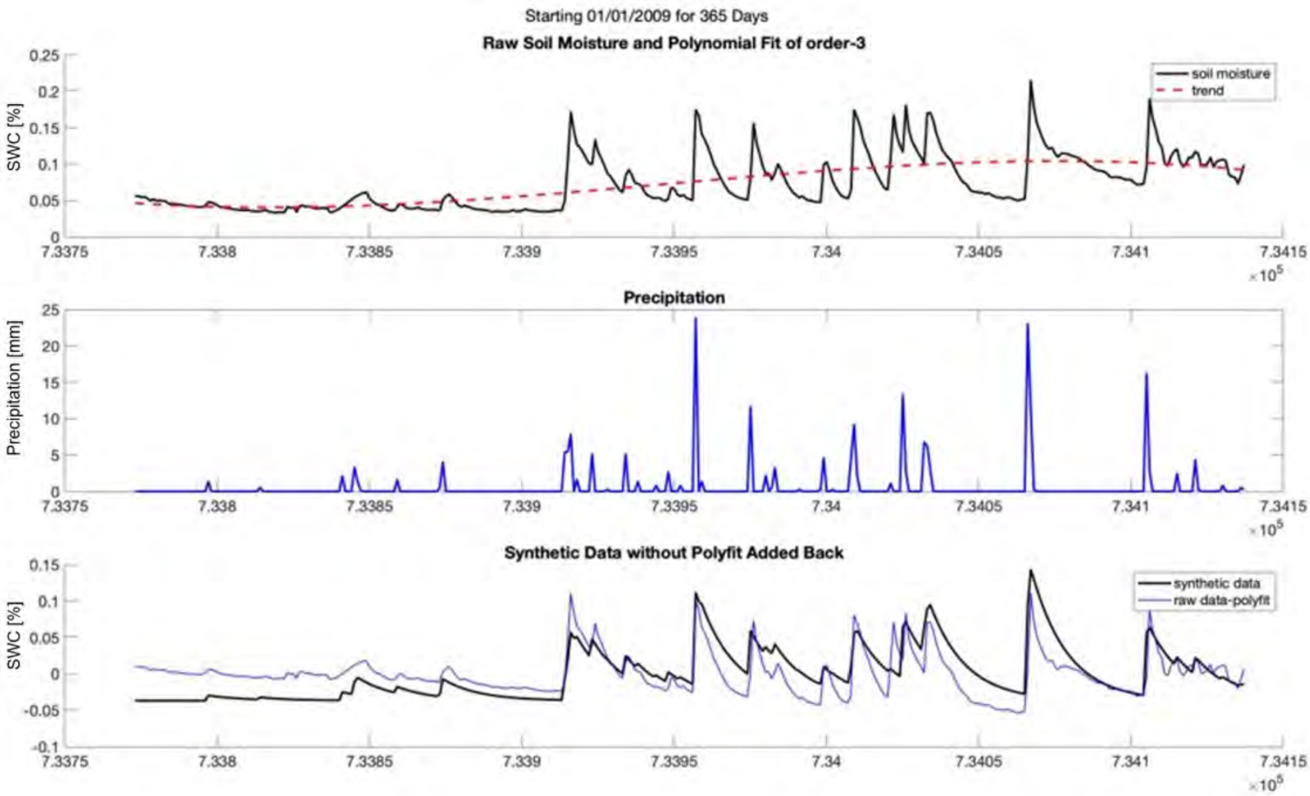

Fig. 2. Output of the linear fit model that convolves the precipitation time-series with an exponential decay response function. The top plot shows SES 2 cm soil moisture data in black, and the long-term polynomial trend that was removed in red. The middle plot shows the precipitation time-series. The bottom plot shows the SES data with the polynomial fit removed in blue, and the simulated data in black.

like hysteresis, and makes the equation difficult to solve numerically.

There are several solutions to the Richards Equation, and we use the Van Genuchten-Mualem model, a solution commonly used to model soil water content [9]. The Van Genuchten-Mualem model is given by the following two equations:

$$S = \frac{\theta - \theta_r}{\theta_s - \theta_r} = \frac{1}{[1 + (\alpha h)^n]^m} \tag{4}$$

$$k(\theta) = k_s \left(\tfrac{\theta-\theta_r}{\theta_s-\theta_r}\right) \left[1 - \left(1 - \left(\tfrac{\theta-\theta_r}{\theta_s-\theta_r}\right)^{\frac{1}{m}}\right)^m\right]^2 \tag{5}$$

Together these equations model the water content and the water conductivity as a function of the pressure head. The equations have a total of 5 parameters, which all impact the relationship between the three variables. θ_r is the residual water content, the amount of water still present in the soil even at high temperatures/pressures (the amount of water present in the right diagram of Figure 3). θ_s is the saturated water content: the maximum amount of water the soil can hold (the amount of water present in the left diagram of Figure 3). Equation (4) solves for the saturation S a non-dimensionalized and normalized measure of water content (while θ goes from θ_r to θ_s, S goes from 0 to 1). The water content depends on the pressure head h, where the scaling parameter α and exponential parameter n define the relationship between the two. The m parameter is defined by n as follows:

$$m = 1 - \frac{1}{n} \tag{6}$$

The fifth parameter is k_s, the saturated hydraulic conductivity, which defines the maximum water conductivity that occurs when the soil is fully saturated. These parameters define the relationship between pressure head, water content, and water conductivity, which can be summarized in the water retention curve, an example of which is shown in Figure 4.

The fact that there is a dependence between water content and water conductivity in the model lead to nonlinear effects, including hysteresis. Hysteresis is

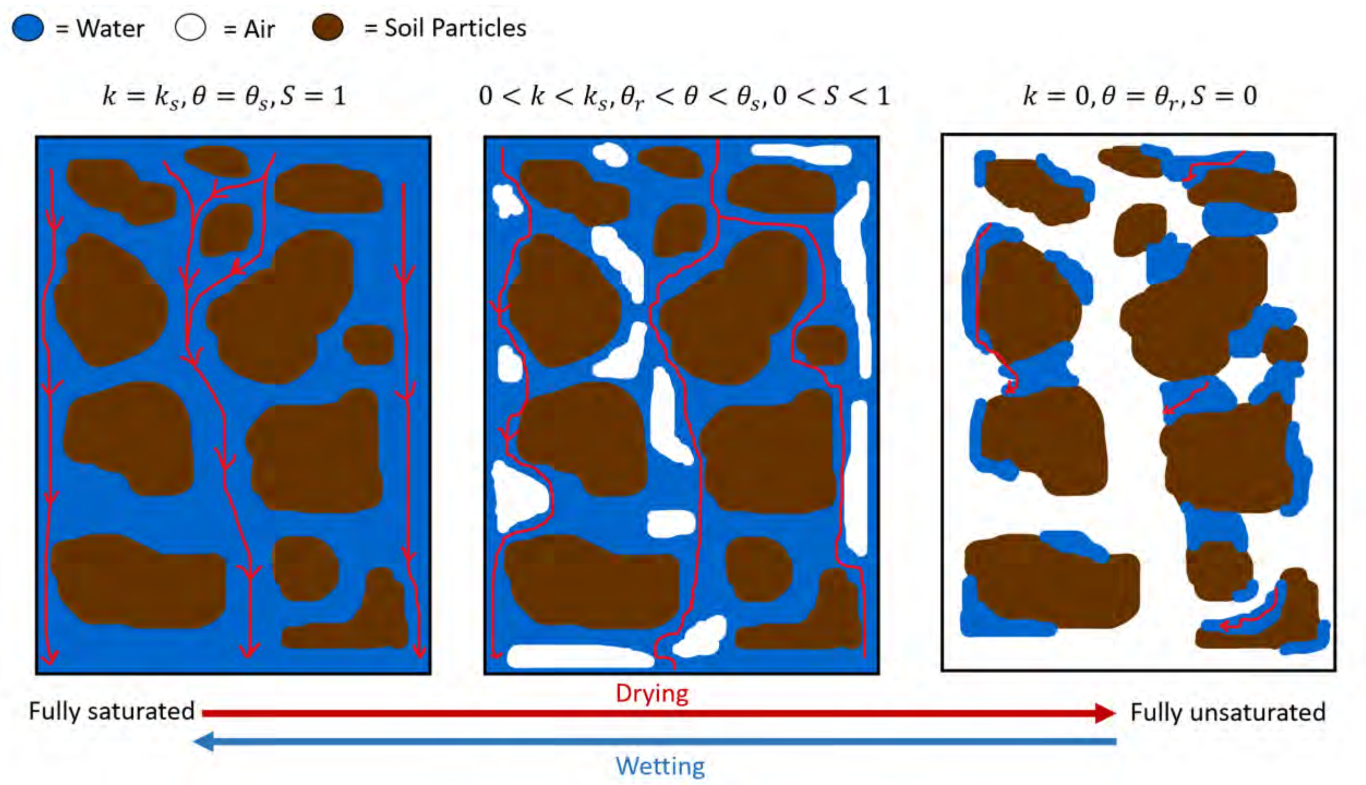

Fig. 3. Cartoon showing the three material system, consisting of soil particles, water, and air. The left diagram shows fully saturated soil, where the water content and water conductivity are at their maxima ($\theta = \theta_s$ and $k = k_s$). The middle pannel shows an intermediate stage, where air has begin to enter, and both the water content and water conductivity are lower. The right panel shows the residual water case, where the maximum amount of water has left the soil, and the water conductivity has gone to zero ($\theta = \theta_r$ and $k = 0$). The red arrows are examples of paths for water to flow through.

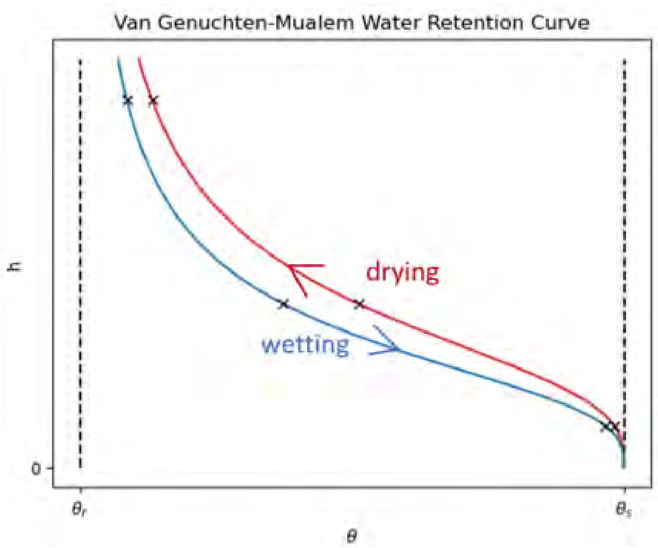

Fig. 4. Example of the Water Retention Curve for a given set of parameters α, n, k_s, θ_r, and θ_s. θ_r and θ_s define the limits of the curve, and α, n, and k_s define the curve's steepness and shape. The red and blue curves show the effect of hysteresis- the history of the system changes the state of the system, even when all parameters are the same.

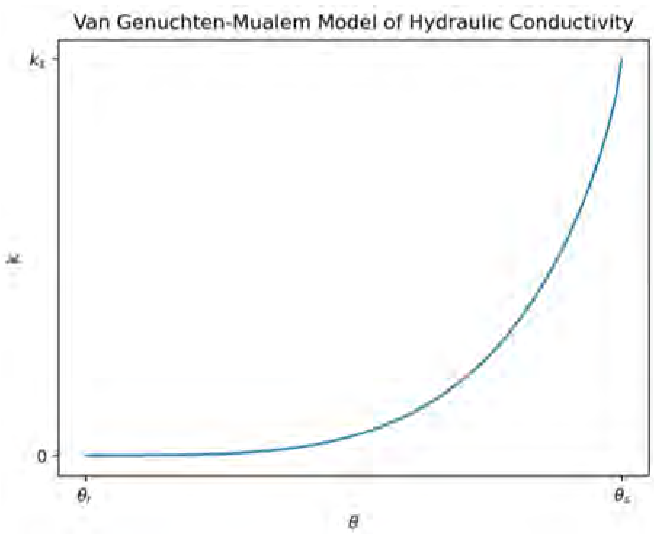

Fig. 5. Example of the relationship between the soil water content θ and the soil water conductivity k. As water content goes from the residual water content θ_r to the saturated water content θ_s, the conductivity goes from 0 to the saturated water content k_s. The shape of the curve is defined by α and n.

the dependence of the system's state on the history of the system. For our case, it means that the water conductivity and water content for a given pressure head depends on what the pressure head has been in the past, or whether the soil is drying or wetting (Figure 4). We can also think about it in terms of precipitation events: the soil water response to a particular precipitation event will depend on whether the last event was the previous day, week, or month. These hysteretic effects are an important reason why our linear model failed to accurately replicate our data.

B. HYDRUS 1-D and Phydrus

In order to use the Richards Equation to model soil water content from our data set, we need to be able to relate precipitation to the pressure head, and need to solve the equation over time. HYDRUS 1-D is a program that solves the Richards Equation in one dimension, and can take a precipitation time series as an input [10]. For a given set of parameters and a precipitation time-series, HYDRUS will construct a time-series of soil water content at a given depth by numerically solving the Richards Equation using the Van Genuchten-Mualem model.

For our work we used Phydrus, an open-source implementation of HYDRUS 1-D as a Python module [11]. This allowed us to more quickly implement various conditions into the HYDRUS model without using the GUI that is used in HYDRUS 1-D.

C. Fitting the Data

Windows were chosen that had multiple precipitation events to better test the parameter fit. For data in each window, a moving average was used to smooth the half hourly data over 4 points to reduce noise from the detectors, resulting in data points every 2 hours. Phydrus discretizes the soil column in the Z direction, and columns were built to be 80 cm deep with 160 nodes. The column was composed of a single, uniform soil. Phydrus was also set to output Soil Water Content at 2-hour intervals over the window, to align with the smoothed data set. To compare the fit, the root mean squared (RMS) value was calculated between the smoothed data and the Phydrus prediction.

To model the data, parameters were adjusted by hand until the simulated SWC accurately modeled the data, and any adjustment in the parameter values

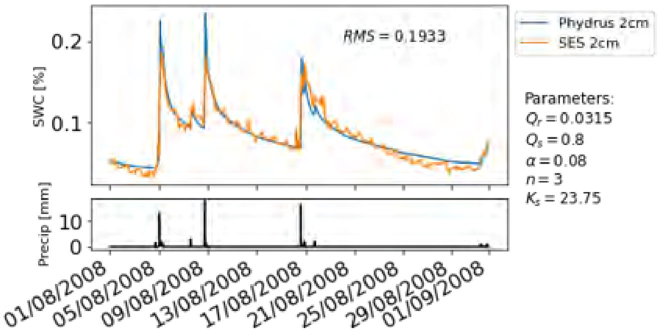

Fig. 6. An example of a one month window from August 2008 fit with Phydrus. The bottom plot shows half hourly precipitation events in black, and the top plot shows moisture measurements at 2 cm at US-SES in orange, and the modeled data in blue. Parameters used are listed on the right. Although the fit is not perfect, the 1-D physical model does a much better job than the linear model.

lead to an increase in the RMS value. An example of a fit found for a 1 month window is shown in figure 6.

D. Parameter Grid Search

To better understand the nonlinear relationships between the five parameters used in the Van Genuchten-Mualem model, a gridsearch was performed in parameter space around the best fit for the August 2008 window. Starting with the parameters listed in Figure 6, the values of 2 parameters were varied at a time, and the log-likelihood function of the parameters given the data was plotted (Figure 7). The nonlinear relationships shown in these plots illustrates the difficulty in finding the optimal parameters to model the given data, as it becomes difficult differentiating the global minimum from local minima. The location of the yellow stars show how an optimal fit must find a balance in the full 5-D parameter space, which may not align with the best fits in the 2-D parameter spaces shown.

IV. Results

Best fits were found for 3 one-month windows in the summer of 2008, 2013, and 2018, giving a total of 9 windows (Figure 8). Summer windows were chosen to model soil moisture response during the monsoon season, a period of relatively frequent precipitation events [12]. Windows with multiple precipitation events were chosen to avoid overfitting the response to a single event. Each window has a comparably low RMS value (the lowest was

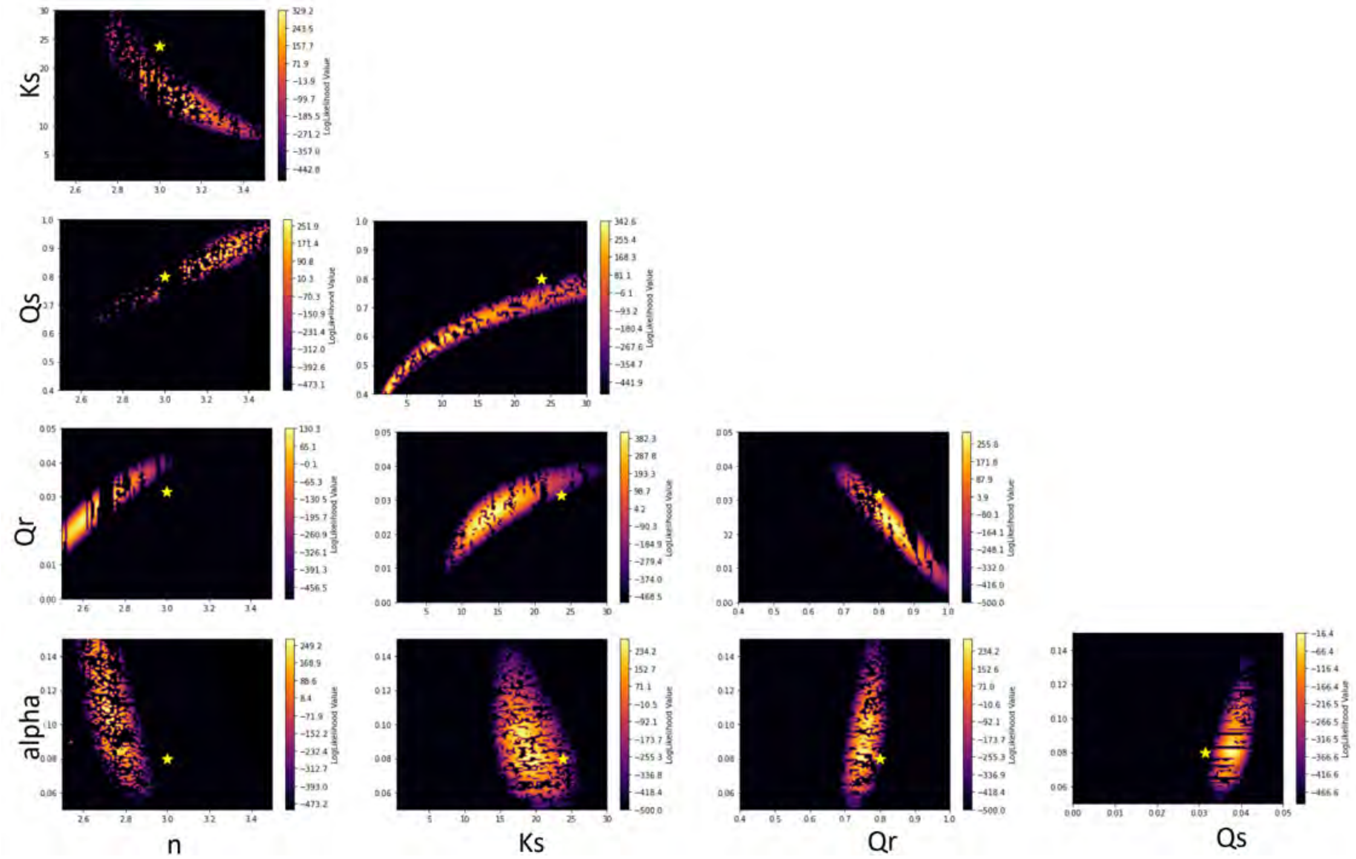

Fig. 7. Plots in parameter space of the log-likelihood function of the parameter values given the data set. Each plot shows the trade off between each parameter pair when varied around the best fit for the August 2008 shown in figure 6. The yellow stars show the parameter values that represent the best overall fit found.

found for August-September, 2018), suggesting relatively good fits.

These fits were used to see if there are long-term trends in parameter values over time. Figure 9 shows these fits in parameter space, showing how these parameters vary between windows. The arrows show the general trend the parameters appear to follow between 2008, 2013, and 2018. There is a decrease in the exponential term n, and the saturated conductivity K_s, and there is an increase in the saturated water content Q_s.

V. Conclusions

The RMS values for the plots shown in Figure 8 suggest that the SWC at a depth of 2cm can be accurately modeled using the Van Genuchten-Mualem model. Figure 9 shows that there are long-term trends in parameter values, where the variability within each year is smaller than the total variability. This suggests that the changes in parameters represent a real change in the soil water response, which could be due to changes in soil properties. The fact that these changes occur over a similar time-frame as climate change suggests that the two are correlated.

The one dimensional model is still an approximation of the system that leaves out important three dimensional effects, meaning that it will not be a completely correct model. However, finding systematic, long-term variation in the model's parameter values offers a way to study long-term change in soil properties.

The decrease in K_s supports the prediction from Hirmas et al., who predicted a decrease in saturated water conductivity due to an increase in macroporosity [4]. The decrease in n and increase in Qs also support change in soil properties between the years, although it is not clear whether these changes are connected to soil macroporosity or are due to another effect.

Decrease in saturated conductivity means that it is more difficult for water to infiltrate the soil.

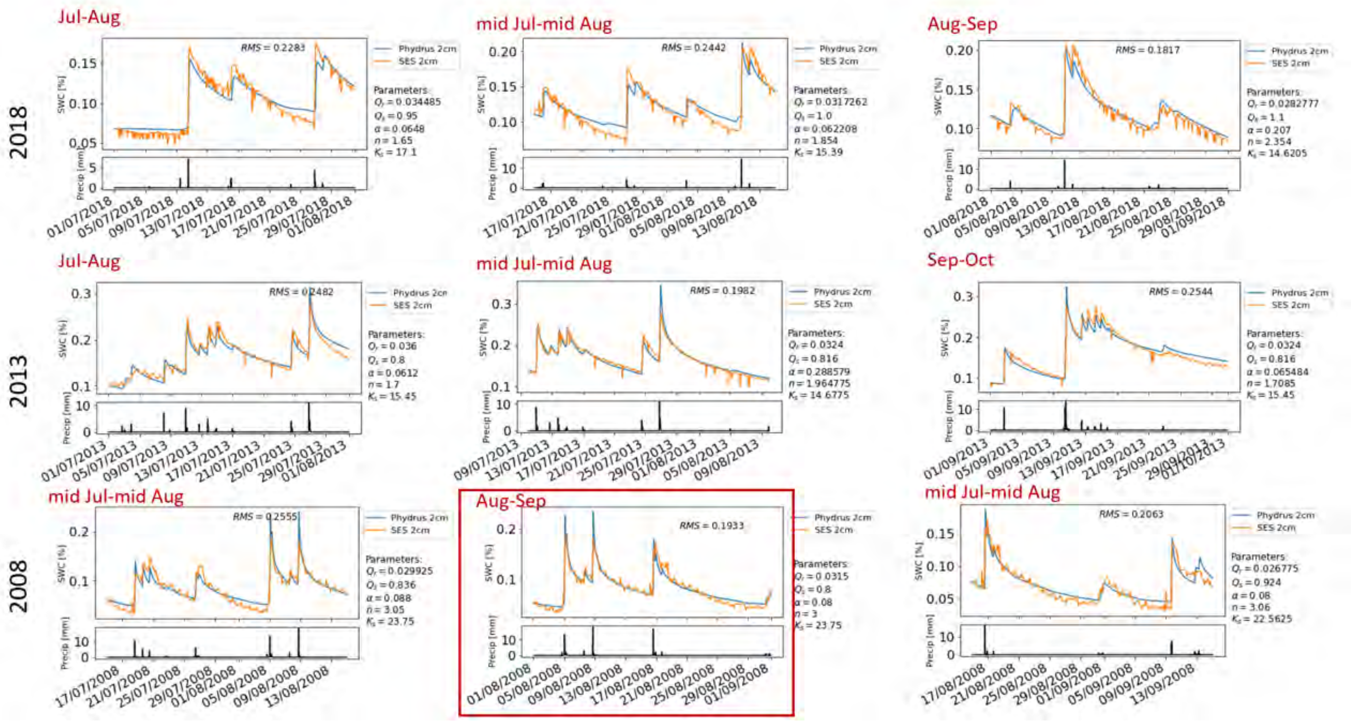

Fig. 8. Nine one month windows where a HYDRUS 1-D best fit was found. Three one month windows were made from the summer in 2008, 2013, and 2018. RMS and parameter values are reported for each plot. The best fit parameters are plotted in Figure 7. Parameter values are relatively similar between windows of the same year, but there is a significant decrease in n and K_s from 2008 to 2013, and an increase in Q_s from 2013 to 2018.

Coupling this with the increase in more extreme precipitation events followed by longer periods of drought would mean an even greater reduction in ecosystem water availability and more runoff [3][4]. The SES site receives an average of 270 mm (10.75 in) of precipitation per year, making water one of the most important limiting factors in the ecosystem. Any decrease in water availability will have profound consequences for the organisms that inhabit this landscape.

A. Future Work

In order to further these findings, I plan on finding the best fits for more windows across the data set. This will allow us to build a set of time-series for the parameters themselves, which would allow us to more clearly see these changes.

Changes in three dimensional effects, due to things like changes in vegetation growth or change in landscape due to erosion, could lead to changes in soil moisture response that the one dimensional model fails to capture. Modeling the soil moisture response at other sites in the Sevilleta (the Litvak Lab has a total of 3 sites at the Sevilleta where they have been collecting data for comparable amounts of time) would help determine whether the changes in parameter values are due to changes in soil properties correlated with climate change or whether they are due to changing 3-D conditions. If we find similar trends across the sites, the changes must be due to something impacting all of them, and we can rule out 3-D effects.

I plan on finishing a Bayesian Monte Carlo algorithm that can sample the 5 dimensional parameter space and assist in finding the best fits for a given window. This will help automate the process, allowing us to produce time-series of parameter changes for other sites. The Litvak Lab has sites in seven of New Mexico's ecosystems, ranging from elevations of 1593 meters (5225 feet) to 3000 meters (10,000 feet) and annual precipitations from 270 mm (10.75 in) to 650 mm (25.5 in). Modeling the long-term changes in soil properties at each of these sites would give us a comprehensive view of soil-properties across New Mexico.

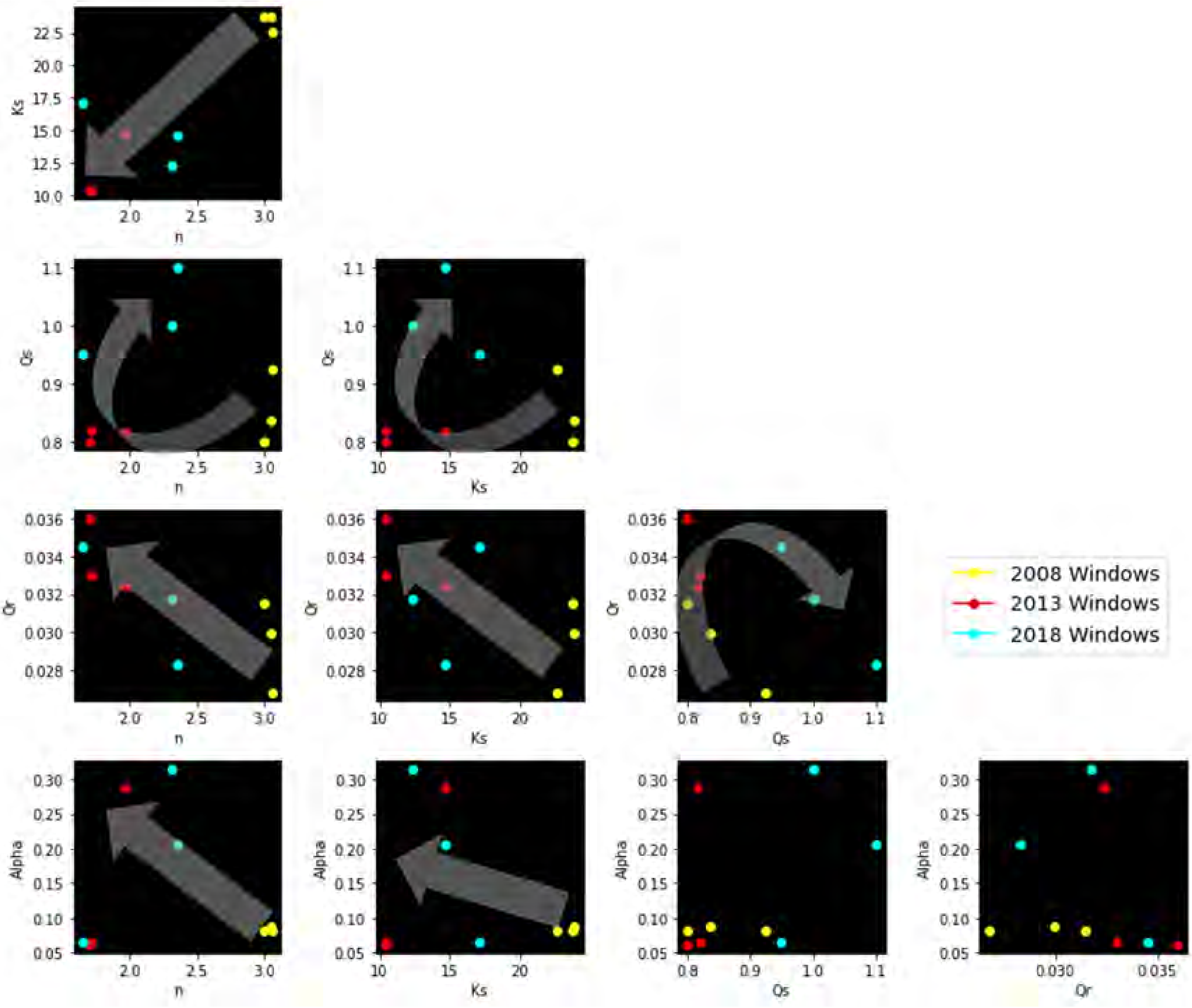

Fig. 9. Plots in parameter space of the best fit values for the nine windows shown in figure 8. Arrows indicate the general trend the parameters appear to follow between 2008, 2013, and 2018. There appears to be a general decrease in the exponential parameter n, and the saturated conductivity K_s, as well as an increase in saturated water content Q_s.

VI. Acknowledgements

I would like to thank my advisor Dr. Mousumi Roy for her guidance and support throughout this project. I would also like to thank the UNM Geophysics group for their insight and support, Joey Sorenson for his contributions to the project, especially when building the linear model. Special thanks to the Litvak Lab for sharing data with us, and specifically to Dr. Marcy Litvak and Dr. Tomer Duman for offering their thoughts and input on the project. Thanks to Rachael Auer and Mikael Schlumpf for their guidance and patience with my questions while in the field. Finally, I would like to thank the Rayburn Reaching Up Fund and the Sustainable Water Resources Grand Challenge Initiative for providing funding for this project.

References

1. Hansen, J., Ruedy, R., Sato, M. & Lo, K. Global surface temperature change. *Reviews of Geophysics* **48** (2010).
2. Stocker, T. *Climate change 2013: the physical science basis: Working Group I contribution to the Fifth assessment report of the Intergovernmental Panel on Climate Change* (Cambridge university press, 2014).
3. Archer, S. R. & Predick, K. I. Climate change and ecosystems of the southwestern United States. *Rangelands* **30,** 23–28 (2008).

4. Hirmas, D. R. *et al.* Climate-induced changes in continental-scale soil macroporosity may intensify water cycle. *Nature* **561,** 100–103 (2018).
5. Huntington, T. G. Evidence for intensification of the global water cycle: review and synthesis. *Journal of Hydrology* **319,** 83–95 (2006).
6. Jung, M. *et al.* Recent decline in the global land evapotranspiration trend due to limited moisture supply. *Nature* **467,** 951–954 (2010).
7. Lagarias, J. C., Reeds, J. A., Wright, M. H. & Wright, P. E. Convergence properties of the Nelder–Mead simplex method in low dimensions. *SIAM Journal on optimization* **9,** 112–147 (1998).
8. Richards, L. A. Capillary conduction of liquids through porous mediums. *Physics* **1,** 318–333 (1931).
9. Van Genuchten, M. T. A closed-form equation for predicting the hydraulic conductivity of unsaturated soils. *Soil science society of America journal* **44,** 892–898 (1980).
10. Simunek, J. *et al.* HYDRUS-1D. *Simulating the one-dimensional movement of water, heat, and multiple solutes in variably-saturated media, version* **2** (1998).
11. Collenteur, R., Brunetti, G. & Vremec, M. *Phydrus: Python implementation of the HYDRUS-1D unsaturated zone model* version 3.8.2.
12. Adams, D. K. & Comrie, A. C. The north American monsoon. *Bulletin of the American Meteorological Society* **78,** 2197–2214 (1997).