Utah State University

DigitalCommons@USU

Undergraduate Honors Capstone Projects | Honors Program

5-2020

Designing Technology for Different Scales of Irrigation Scheduling

Paolo Alexander Consalvo
Utah State University

DESIGNING TECHNOLOGY FOR DIFFERENT SCALES OF IRRIGATION SCHEDULING

by

Paolo Alexander Consalvo

Capstone submitted in partial fulfillment of the requirements for graduation with

University Honors

with a major in

Civil Engineering

in the Department of Civil and Environmental Engineering

Approved:

Capstone Mentor
Dr. Alfonso Torres-Rua

Departmental Honors Advisor
Dr. Laurie McNeill

Committee Member [optional: type name or N/A]
N/A

University Honors Program Director
Dr. Kristine Miller

UTAH STATE UNIVERSITY
Logan, UT

Spring 2020

ABSTRACT

Uncertainty in water availability is a significant challenge to the agriculture industry. Farmers and irrigators depend on novel uses of sensors and data to maximize water efficiency. Documented studies have demonstrated scheduling irrigation is a straightforward, deterministic means of achieving water efficiency. Irrigation scheduling uses several parameters to determine the moment of crop water stress due to available water in the soil. However, sensors and data for soil moisture and matric potential, a parameter describing water available to plants, have the potential to train machine learning algorithms to forecast water irrigation needs based on previous measurements. Satellite remote-sensing is another developing technology that describes the environmental conditions that enable irrigation scheduling and provides data on crop health by allowing for calculations on collected field images.

This project trains a learning machine with soil moisture and home-brew tensiometer information. To create a water management system that avoids exposing crops to stress, the learning machine uses previous soil water conditions to forecast crop water demand. This machine learning model informs the farmer of the moment maximum water depletion will occur, providing the farmer opportunity to irrigate in advance of crop water stress conditions. Additionally, this research evaluates the value of soil moisture, matric potential, and trained machine learning against characteristics of the specified agricultural undertaking. Because larger agricultural undertakings can be managed with remote-sensing of crop health, this research investigates the viability of ground-sensing against satellite remote-sensing. Sensor-improvements would be more viable for an urban agriculture system. Understanding scenarios in agriculture to tailor technological development will allow farmers to further maximize crop yield and quality with their increasingly limited water availability.

Key Words: Agricultural Water Management, Machine Learning, Remote-Sensing

ACKNOWLEDGMENTS

This study was conducted with support from the USU Honors Program, Community Engaged Scholars Program, and Undergraduate Research Fellowship. Funding was provided by a USU Honors Program Research Fund Award, and the Lawrence O. Cannon Award. This project was presented at Utah Research on Capitol Hill, and photos can be requested by contacting consalvopaul@gmail.com.

TABLE OF CONTENTS

LIST OF FIGURES

Introduction

Agricultural water management is necessary for a world constantly changing regarding spatiotemporal availability of water. Scheduling irrigation is a straightforward means of managing agricultural water, and has been undertaken deterministically using collectable data, such as wind speed, humidity, and solar radiation. However, machine-learning and remote-sensing are two approaches being further developed at academic and technological levels for increasingly intentional use in agricultural water management. This project uses two case studies on support vector machine (SVM) learning and a case study investigating satellite remote-sensing to identify more specific utility areas for the technology.

Background

Urbanization is increasing globally, and a more urbanized society correlates with higher water use. Estimates from 2018 estimates state predict overall population growth and increases in urbanization will add 2.5 million people to urban populations by 2050 (UNDESA, 2018). Opportunities to conserve water in cities are plentiful, with 25±4% of large cities being under water stress (McDonald et al., 2014). Urban agriculture, growing crops within cities for city inhabitants, can increase global food supply with more efficient land usage due to the projected increase in urban dwellers (McDougall et al., 2018).

Evapotranspiration in urban agriculture varies temporally due to extraneous deterministic parameters like increased wind speeds from building arrangements and changes in shade cover throughout the day. These extraneous parameters need sensors to be tracked. Urban agriculture is undertaken in some less-developed countries (LDCs) to conserve financial capital and increase historically poor food security, and multiple sensors to determine the parameters for evapotranspiration are not within the budget of these undertakers (Mougeot, 2000). Because of this, urban agricultural technology will be analyzed in two technology case studies using machine learning on just moisture sensors and matric potential sensors. The intuition of the irrigator, coupled with the soil moisture and matric potential readings, will schedule the irrigation.

While urban agriculture becomes more prevalent with increasing urbanization, larger scale (at least one acre), rural agriculture has the potential for better water management with satellite remote sensing. Broadband vegetation indices use the near-infrared portion of the satellite's sensed spectrum to determine vegetation health (Agapiou et al., 2012). This project analyzes larger scale, rural agriculture in a case study using remote sensing to evaluate drought identification and the reliability of the multitudes of indices the industry uses.

The normalized difference vegetation index (NDVI) is one of the most used indices for characterizing crop growth and health. This index requires a simple division of the difference between near-infrared light reflectance and red light reflectance by the sum of the light reflectance values. MSAVI2 and WDVI both account for soil background, the appearance of soil in a captured satellite image, and the way this affects the extraction of vegetation data. (Zou & Matti, 2017). Figure 1a shows NDVI displayed over Logan, Utah, an area with typically exposed soil for a captured agricultural satellite image. Figure 1b shows NDVI displayed over San Juan County in New Mexico, an area explained in the methodology as ideal for this research's case study due to its high drought indices, measured water salinity due to erosion, and soil background not covered by vegetation. The known soil background differences provide a tool to calibrate the calculation of vegetation indices used in agricultural water management.

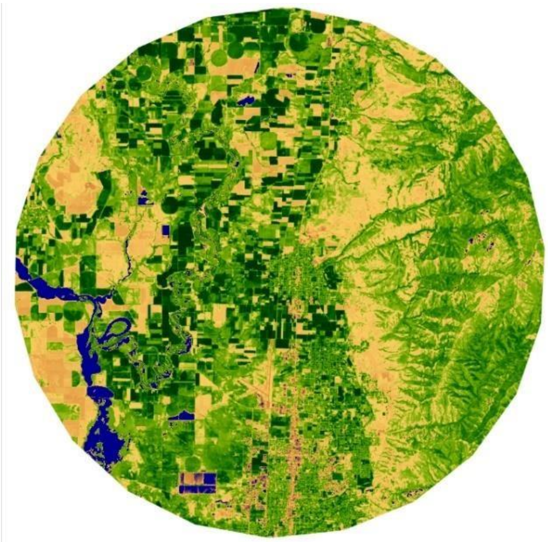

Figure 1a. Logan, Utah NDVI

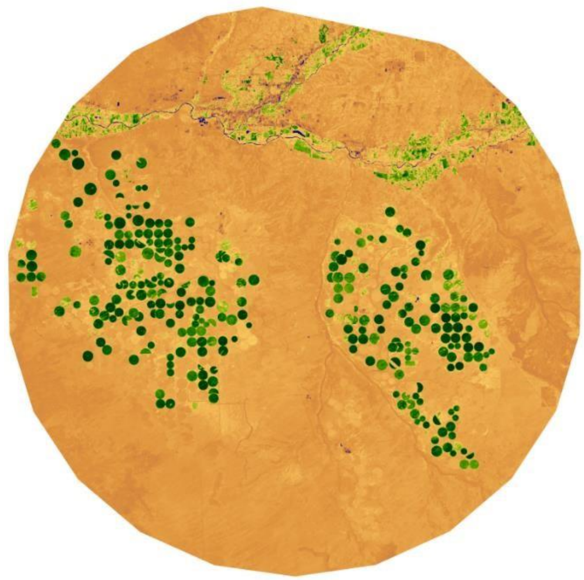

Figure 1b. San Juan County in New Mexico NDVI

A parameter L used to formulate the MSAVI2 equation and used as a variable in the WDVI equation is the slope of the soil line, a relationship between red and near-infrared light in a satellite's collected image (Xue & Su, 2017). Multiple methods exist for calculating soil line, such as a method that "slices" the red axis into finite increments and finds the minimum near-infrared value at each (Fox et al., 2004).

Drought identification would better support water management strategies for larger-scale development in arid climates. Katerina Michaelides from the University of Bristol mentions the main effect of climate change is desertification; the inversely related decrease of rainfall with evaporative demand (McSweeney, 2019). Some arid states would even benefit legally from a stronger basis in big-data for their water management. For example, Arizona, California, and Colorado must demonstrate adequate water supply for at least 20 years for zones to be approved for land development (Schreck, 2017). Multiple sources provide access to satellite data, but a more recently developing, programmatically robust, and cloud-based platform for accessing this data is Google Earth Engine.

Google Earth Engine (GEE) is used to access satellite data for manipulation and vegetation index generation. GEE accesses the Landsat and Sentinel collection of satellites, the former being the longest continuously running space-based account of Earth's land-cover data (NASA, 2010).

GEE's viability is evaluated in practice with this project's remote-sensing case study. Both satellites have been calibrated in testing over control sites and are reliable for collecting land cover data at the scales needed for rural agriculture (Sterckx & Wolters, 2019). At larger scales, GEE and remote-sensing and machine-learning are leveraged together to identify crops and forecast crop health rather than soil. (Shelestov et al., 2017; Aboutalebi et al., 2019)

Farmers are generally averse to technological change in the agriculture industry. The industry allows for intuition-based decision-making, but his research reviews areas for practical big-data applications by developing and implementing technology that could benefit farmers in both rural and urban settings. The case studies will practically apply the technologies' principles to provide insight into further potential research in machine-learning and remote sensing.

Methods

Support Vector Machines

Vapnik (1995) describes support vector machines (SVMs) as learning machines effective for classification, but his findings also prove SVMs are effective for regression modeling, the basis of time series prediction. With SVMs, Eq. (1) is continuously tested against the training dataset. In Eq. (1), y is an output vector, T transposes the weighting vector w, x provides the input vector, and b provides a vector that biases inputs. The objective of this model is to alter the w and b vectors to minimize a function outputting an error value.

$$y = f(x) = w^T X\, x + b \tag{1}$$

The SVMs implemented in this study are ε-support vectors in the R programming language's "SVM" library using a Huber loss function. The ε in ε-support vector references the model's insensitive variable ε. In assuming a non-linear model accounting for short-term variations, the radial basis function (RBF) is used in the SVM implementation. ε support vector machines are capable of incurring complexity at a rapid rate, rendering the machines impractical. ε SVMs compare the output vector to the SVM generated vector and use the value of ε to create a function insensitive to both noise and bias, as shown by Eq. 2.

$$|y - f(x)|_\varepsilon = \begin{Bmatrix} 0 & if \quad y - f(x) \le \varepsilon \\ |y - f(x)| & else \end{Bmatrix} \tag{2}$$

Vapnik optimizes the ε insensitive SVM function with a Huber loss function L, which, as shown in Eq. 3, normalizes the regression over time. This allows R to run the machine-learning with significantly fewer estimates than without the loss function (Huber, 1964). Eq. 4 is the optimization for a training function - output difference greater than a parameter c, while Eq. 5 is the optimization for a training function - output difference less than a parameter c.

$$L(y, f(x)) = L(|y - f(x)|_{\varepsilon}) \quad (3)$$

$$L(|y - f(x)|) = c|y - f(x)| - \frac{c^2}{2} \quad (4)$$

$$L(|y - f(x)|) = \frac{1}{2}|y - f(x)|^2 \quad (5)$$

SVMs are not practical for long-term time series prediction. However, seasonal crop data should repeat with slight deviations. The purpose of the SVMs is to provide a model capable of predicting soil moisture depletion for the specific agricultural area accounting for the deviations.

SVMs use classification lines named hyperplanes to identify a feature of a data point the user does not know. By adjusting the hyperplane based on historical data, the SVM model used can increase in reliability for a continuously growing dataset.

Using six datasets from West Weber soil moisture sensors and three trial runs of self-constructed tensiometer data from Utah State University's Student Organic Farm, the ε, Huber-loss SVMs are tested by training on the first seven weeks of the growing season. Starting at day 40 until the end of the season, the SVMs will predict the remaining soil moisture values. Essentially, the SVMs will use soil moisture or matric potential depletion coupled with the intuition of the irrigator to predict values an irrigator could see, compared to a quantifiable threshold, and then use to forecast irrigation events.

Satellite Remote-Sensing

Landsat 8 satellite data is accessed through GEE to manipulate the associated image rasters. Remote-sensing for agricultural purposes is fundamentally based on developing indices to show a farmer's spatial and temporal variation in their crop health; this case study will script Google Earth Engine to compare multiple accepted vegetation indices. The purpose of this case study is to find a gap in current remote-sensing methodologies to determine areas for technological development for larger-scale undertakings.

The multitudes of indices used in the industry make this case study investigate a time-dependent variable that would make the indices perform differently against each other. The chosen variable is the soil background, which alters the relation of red to near-infrared light reflectance. Desertification results in a change in this variable, so global desertification trends are examined to find a study area.

New Mexico's San Juan River Watershed provides land for agricultural plots. The northwestern corner of the state within the watershed has approximately 100,000 acres of farmland, primarily with center-pivot setups. The high salinity of the southern reaches of the Colorado River, higher wind speeds, and noticeable long-term erosion patterns make this northwestern sector of New

Mexico an ideal case study location to compare the three soil-dependent indices' change due to desertification.

The three vegetation indices GEE compares are NDVI, WDVI, and MSAVI2. NDVI uses Eq. 6 to relate near-infrared light to red light. MSAVI2's empirical assumption of the soil-line adjustment makes Eq. 7 the accepted relation between near-infrared light and red light for this index. WDVI requires the determination of the soil line by plotting red pixel values against near-infrared pixel values. The slope of the line, L, is used to calculate the index with Eq. 8.

To quantify desertification over time, desertification is assumed to relate to drought patterns. The US Drought Tracker is used to obtain San Juan County drought time series data. Drought is hypothesized to linearly relate to the value changes between the indices. The Landsat 8 imagery is collected to correspond to the US Drought Tracker collection times, as seen in a time series sample in Table 1. Drought scenarios D0 - D4 over San Juan County's land area are provided.

$$NDVI = \frac{NIR-R}{NIR+R} \tag{6}$$

$$MSAVI2 = -\frac{(2*NIR+1)-\sqrt{(2*NIR+1)^2-8*(NIR-R)}}{2} \tag{7}$$

$$WDVI = NIR - L*R \tag{8}$$

The need for an intuitive technology for agricultural use makes this case study investigate the usability of the GEE platform. The Google Earth Engine platform requires code input in JavaScript. However, GEE has recently championed a Python application programming interface (API). The Python API allows the user to download GEE satellite data from outside the usual GEE web host. For this project, the platform HydroShare, developed by Utah Water Research Laboratory researchers from Utah State University (USU), will be used to construct a Python applet a farmer can use to specify their desired farm satellite images without needing to write any computer code.

Table 1. San Juan County Percent Land Area Afflicted By Drought Scenarios

Week	No Drought	D0-D4	D1-D4	D2-D4	D3-D4	D4	DSCI
5/14/2013	0	100	99.04	97.63	81.68	44.14	423
10/14/2014	16.7	83.3	62.64	30.04	8.08	0	184
11/3/2015	73.76	26.24	6.21	0	0	0	32
7/12/2016	23.15	76.85	15.62	0	0	0	92
6/13/2017	78.55	21.45	6.56	0	0	0	28
6/5/2018	0.1	99.9	99.04	88.42	61.99	18.17	368
10/8/2019	60.03	39.97	18.07	7.58	0	0	66

Results

Support Vector Machines

Unfortunately, the tensiometers provided data that did not track typical water demand from crops. The hypothesized reason is the USU Student Organic Farm waters during its season based on predetermined scheduling times or visual inspection of the field. A beneficial study would base irrigation scheduling only on the tensiometer's identified matric potential depletion. Using machine learning on data collected for irrigation events based on tensiometer matric potential readings could allow the SVM to categorize predicted tensiometer values as requiring irrigation.

The West Weber soil moisture case study results are shown in Figures 2a through 2f. Each Figure corresponds to a sample. The highest errors for the predicted values were in Sample 5, with a 5.2% error, Sample 4 with a 3.1% error, and Sample 1 with a 3.0% error.

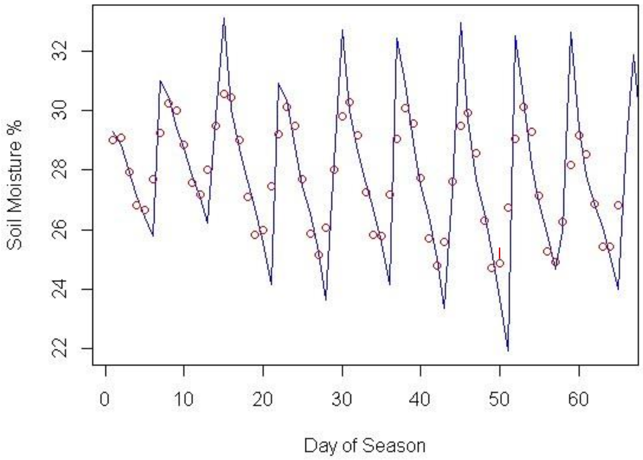

Figure 2a. Sample 1 for SVM Testing

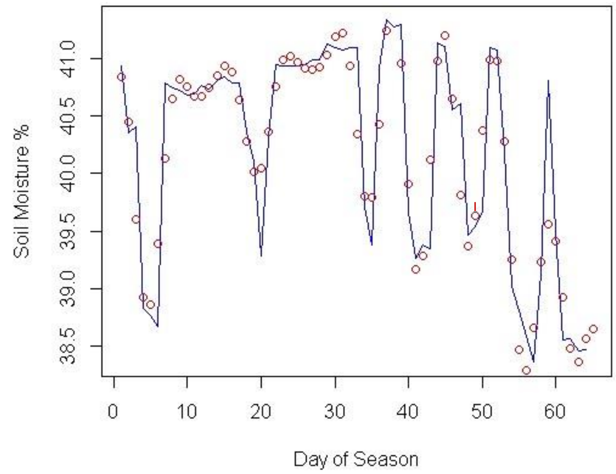

Figure 2b. Sample 2 for SVM Testing

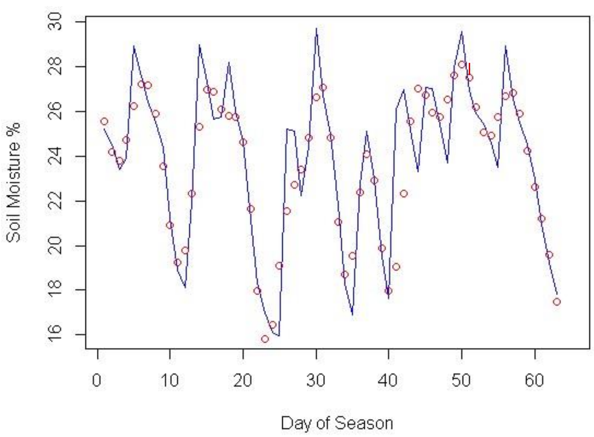

Figure 2c. Sample 3 for SVM Testing

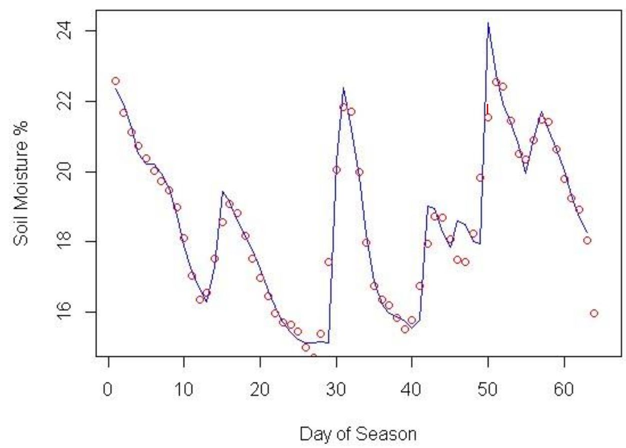

Figure 2d. Sample 4 for SVM Testing

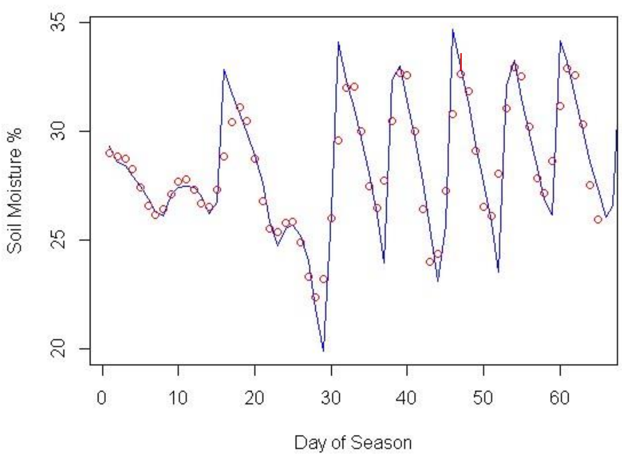

Figure 2e. Sample 5 for SVM Testing

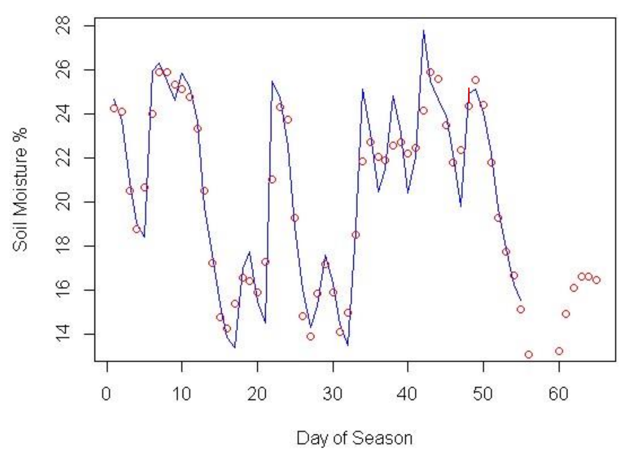

Figure 2f. Sample 6 for SVM Testing

Satellite Remote-Sensing

A “slicing” method on a plot of NIR vs. Red bands with an interval of .005 on the axis of red values allows for effective calculation of the soil line. The Google Earth Engine Python API allows the user to input the desired satellite image to have processed according to the methodology in Figure 3.

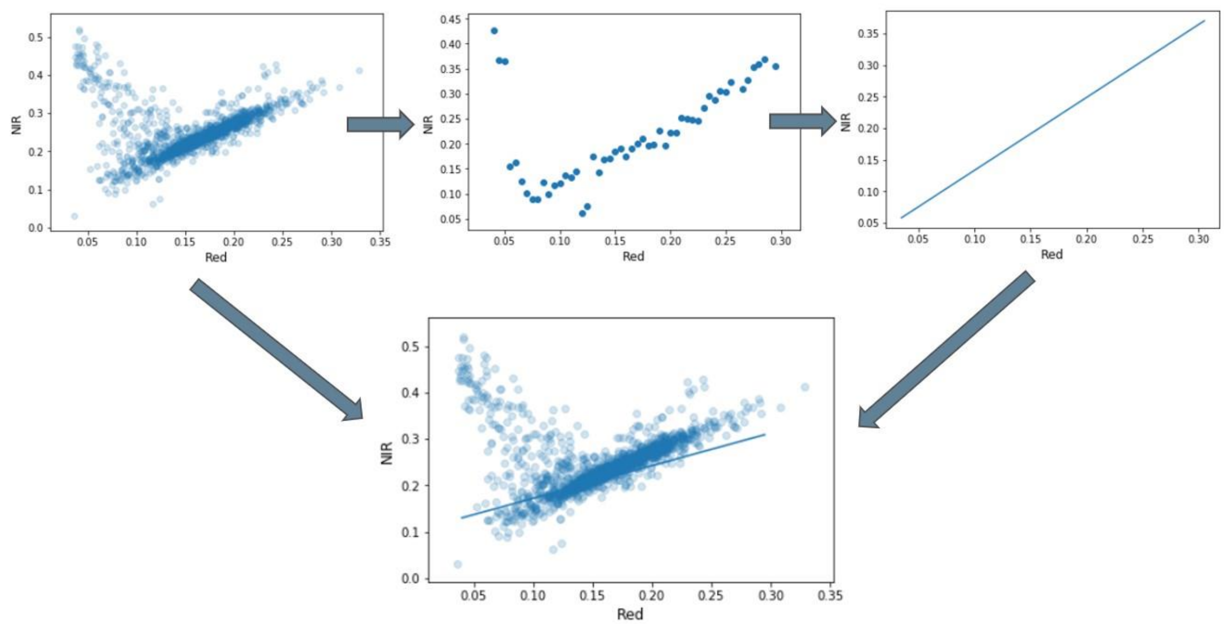

Figure 3. Slicing Method For NIR vs. Red, Resulting In A Linear Regression Line Used As Soil Line

Figures 4a through 4c show sample plots of the vegetation indices for San Juan County. WDVI’s difference from NDVI confirms our hypothesis because the difference occurs for drought years 2013 and 2018. However, MSAVI2 does not differ significantly in its values or distribution. We cannot conclusively attribute drought to erosion and desertification; more time spent with this project in the JavaScript API can allow for higher quantities of image iteration that can quantify this uncertainty. The conclusive differences between WDVI and NDVI confirm the soil line calculation was correct, even though it never appeared to follow the bottom boundary of the scatter plot as other research on soil line describes.

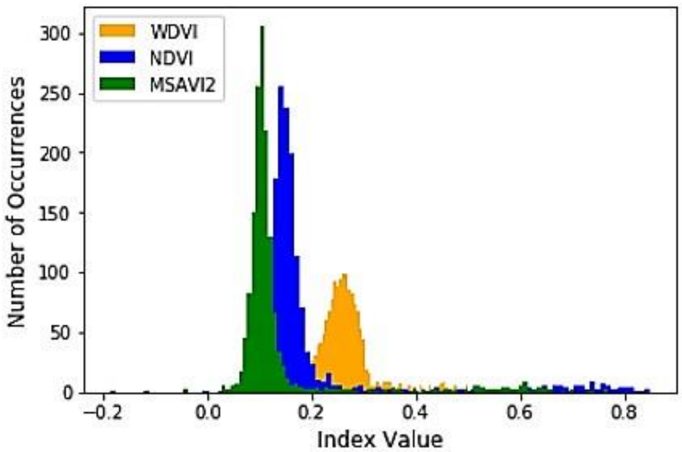

Figure 4a. Plot of NDVI, WDVI, and MSAVI2 Values for a 2013, D4, Drought-Afflicted Image Region

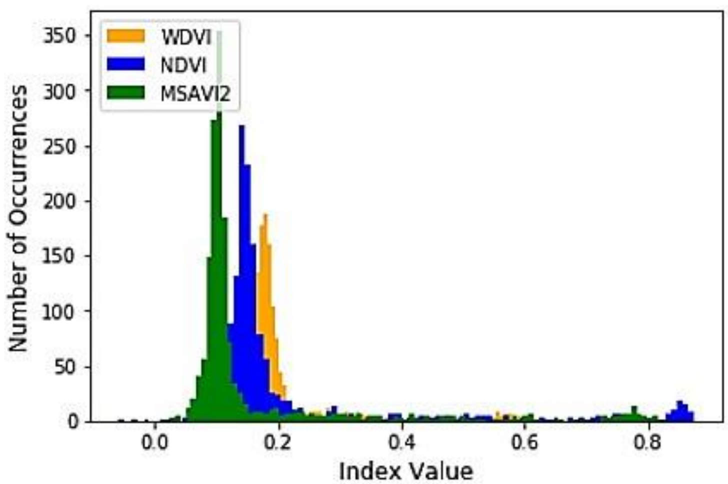

Figure 4b. Plot of NDVI, WDVI, and MSAVI2 Values for a 2016, Drought Un-Afflicted Image Region

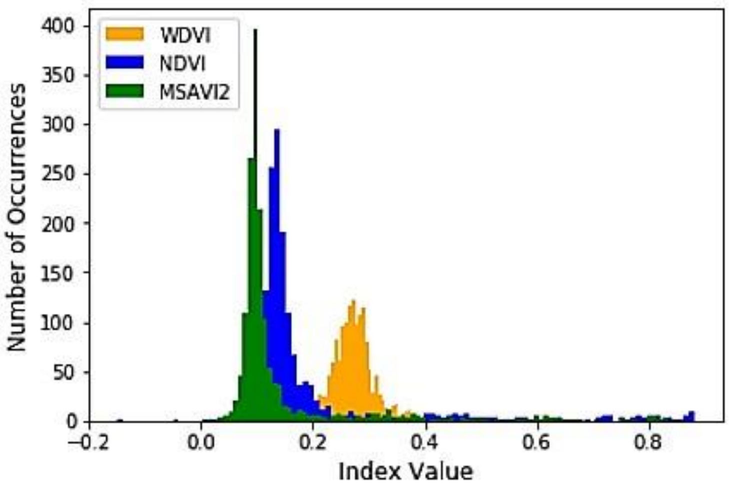

Figure 4c. Plot of NDVI, WDVI, and MSAVI2 Values for a 2018, D4, Drought-Afflicted Image Region

Furthermore, this uncertainty uncovers a beneficial procedural change in agricultural water management; the development of vegetation indices should occur both by spatial change and temporal change. Adjusted vegetation indices already account for soil background, spatial change, but the soil line, as shown in Figure 3, does not match the bottom boundary of the data. Because this soil line does not follow an academically accepted trend but appears to function correctly, new studies could determine a parameter for adjusting indices based on the temporal change of the soil line. Many methods for calculating soil line exist, so those that do not appear like accepted soil lines, like the line in Figure 3, can still be useful if adjusted against other soil lines calculated in the same satellite image region.

The Google Earth Engine Python API can be leveraged for investigating understood image sets in a Web App environment. Lack of widget functionality can make use tougher for those not familiar with computer code, the intended audience of this investigation. A Jupyter Notebook named DroughtOut was successfully implemented and allowed the user to process and generate the results in Figures 4a and 4c without writing any computer code.

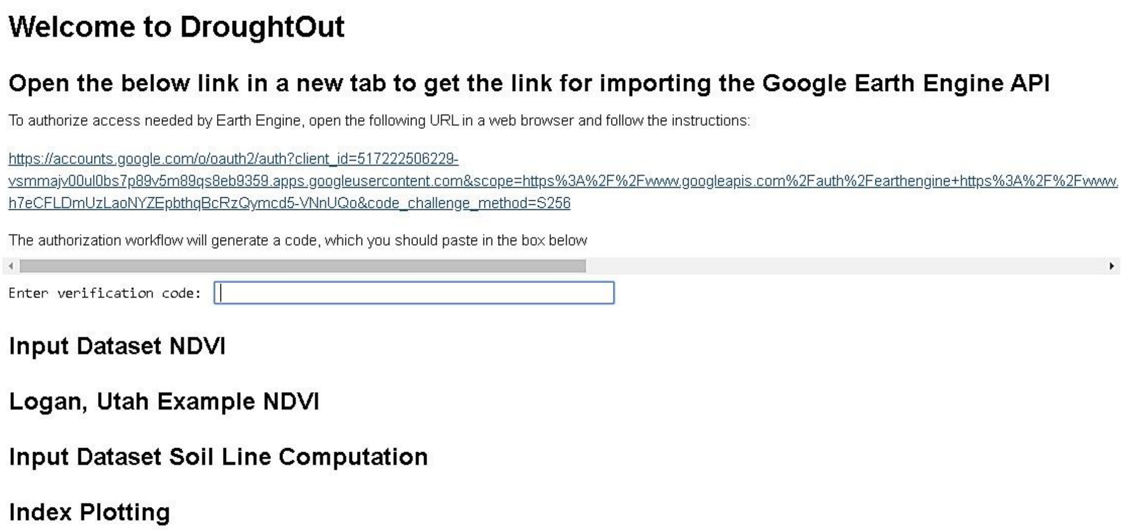

Figure 5. Python Web App Interface Providing Farmer Access to GEE

Word Count: 2770

Conclusions

Urban agriculture can use machine-learning to investigate unknown water depletion parameters and predict water demand without requiring typical sensor technology. A single moisture sensor can use support vector machines to learn on data that accounts for all evapotranspiration parameters and the intuition of the irrigator. Using plots of predicted data, an irrigator can forecast their next irrigation events by comparing the predicted soil moisture value with the previous values they irrigated at. Unfortunately, the model became unreliable when the tensiometer case study did not have irrigation scheduling based on the tensiometer. This result provides new potential for studies in agricultural water management that can analyze the types of sensors that could schedule irrigation if coupled with intuition-based irrigation scheduling. For urban agriculture in areas with less financial capital, such as LDCs, needing only one type of sensor can significantly benefit the capital investment to the farming undertaking.

Remote-sensing methods provide access to increasingly higher-quality land cover data that can locate faulty irrigation heads, mechanical issues, and erosion. Heuristic indices generated by remote-sensing of spectral raster data are better tailored to a longer-term analysis of specific geographic regions. An effective way to use soil line without concern for how the area affects soil line variable L's calculation is to compare the calculated values of L over time for the specific geographic region. This temporal change can effectively tune a vegetation index for a specific field. The variation in the raster value distributions makes the temporal change in the crop marks important in addition to the spatial characteristics.

REFLECTION

This capstone project allowed me to combine my Civil Engineering major, Computer Science minor, and experiences in community service to make a unique contribution to the field of irrigation engineering. I felt empowered to dive into a specialization of the Department of Civil and Environmental Engineering that is usually pursued solely for graduate studies, but I was able to have enough correspondence with my mentor, Dr. Alfonso Torres-Rua, to tailor my undergraduate studies to that specialization.

My relationship with Dr. Torres-Rua provided me meaningful interactions that helped me decide on my career trajectory after graduating. By pursuing graduate studies, I could directly continue the work my capstone project proves needs to be done in the specified technological areas of machine learning and satellite remote-sensing. However, the route of study I chose allowed me to become exceptionally proficient with data analysis, and Dr. Torres-Rua always provided me outlets in industry where I could apply my skillset, even if not in irrigation work. After settling on a job for after graduation, Dr. Torres-Rua had a discussion with me about how to encourage students to experience USU in a way that would lead them down my path of study. I was honored that he put so much effort into engaging in my story, but I also found great joy in learning what he needed as a professor trying to enlist passionate undergraduates he can form future relationships with.

This capstone project started with me building a committee to review my project after completion. Due to the pandemic, I could not provide them my final presentation, but the conversation I had with Dr. Bethany Neilson during the committee-forming phase was one of the most influential conversations I have had; she discussed the implications of a mentor-student relationship as being a weird form of a parental relationship. The way I understood it, the relationship involves trying to make the superior proud of work while the superior provides support and advice, but the lack of emotional boundaries and academic proficiency between both parties makes the output, in an academic sense, more exciting than what would become of a parent’s support of a child. I thought this was a very interesting take on mentor-student relationships, and the amount of support Dr. Torres-Rua provided for my project and my pursuit of funding pushed me harder than some of my course professors even could. Due to the intellectual content of our conversations, I felt an awesome drive to make my mentor proud of my work and excited to expand upon the work. I have had two other mentors while at USU, but the Honors Program’s Capstone experience helped me develop a self-driven project that resulted in the most intellectually stimulating mentor-student relationship I have had at USU.

While my mentor relationship was a unique aspect of my capstone experience, the correspondence of my capstone with the Community Engaged Scholar Program and the USU Student Organic Farm was another exciting facet of the project. I worked as a full-time volunteer for the USU Student Organic Farm between my sophomore and junior years to accumulate around 250 hours for my 400 hour Community Engaged Scholar requirement. This dedication allowed me to establish a relationship with the farm as if I was a paid worker. I needed a capstone for the the Community Engaged Scholar Program, but that would have involved engaging with a community partner, probably the organic farm, to provide a lasting and meaningful project. That specific capstone did not necessarily require a connection to my academics, but the Honors Capstone project motivated me to think critically to apply my academic pursuits. I eventually merged my Community Engaged Scholar Capstone and my Honors Capstone, and I managed to apply Civil Engineering, a field known for contracting and affecting large-scale infrastructure, and scaling the principles to give back to the few-acre organic farm.

To scale the work I was performing, I had to construct my own electronics kits and computer programs to evaluate both the organic farm and West Weber (West Weber being the more useful farm in the report). My computer science minor helped, but I generally had to self-teach many micro-electronics and data-analysis skills to complete this project. While going through the Honors Program, many of my acquaintances questioned the purpose of the transcript designation, and I began to concur with their statements that job opportunities would be the same regardless of the transcript designation. However, when I noticed the substantial increase in my self-learning drive, I very easily understood the worth of the Honors Program and the capstone experience. The reason I joined the Honors Program was to experience something more than my acquaintances in my major. This "more" did not have to be clearly defined; I just wanted a unique route. My capstone reinvigorated my search for this "more" by making me compliment my Civil Engineering skillset with skills I had to provide an additional drive to learn. During my senior year Civil Engineering Design project, we needed a means to cut Styrofoam to form a mold for our project. I very confidently offered to construct a resistive hot wire circuit, one that would allow a user to safely pass a current through a wire, heat the wire, and allow for a robust tool to cut shapes from industrial Styrofoam blocks. I did not have a passion for electronics before this project, but I love them now and am excited to apply the concepts to research studies in my new Transportation Engineering job.

The computer and electronics skills were a fine byproduct of the project, but pondering self-learning brings me to the Honors Program phrase "Dare to Know". It rolls off the tongue, it has a poetic quality, and it makes one excited to learn. However, this project made me reevaluate this phrase. To "dare" to do something implies a daunting nature to it; I was daunted by the learning required of me to complete my capstone. However, this project and the Honors Program seem to embrace daunting learning tasks as exciting. Honestly, I feel a greater comfort in self-learning after this experience even with several other research experiences under my belt. I appreciate what the Honors Program and this capstone have provided me, because having "Dare to Know" be such an important part of the program means the program participants should strive towards feeling excitement in the face of daunting tasks. I hope to take this capstone experience and use it to motivate my future intellectual and personal endeavors.

Word Count: 1083

BIBLIOGRAPHY

Aboutalebi, Mahyar, et al. “Estimation of Soil Moisture at Different Soil Levels Using Machine Learning Techniques and Unmanned Aerial Vehicle (UAV) Multispectral Imagery.” *Autonomous Air and Ground Sensing Systems for Agricultural Optimization and Phenotyping IV*, 2019, doi:10.1117/12.2519743.

Agapiou, Athos, et al. “Evaluation of Broadband and Narrowband Vegetation Indices for the Identification of Archaeological Crop Marks.” Remote Sensing, vol. 4, no. 12, 2012, pp. 3892–3919., doi:10.3390/rs4123892.

Alley, William M. “The Palmer Drought Severity Index: Limitations and Assumptions.” Journal of Climate and Applied Meteorology, vol. 23, no. 7, 1984, pp. 1100–1109., doi:10.1175/1520- 0450(1984)0232.0.co;2.

Consalvo, P. (2019). DroughtOut, HydroShare, http://www.hydroshare.org/resource/948ee00dbaca4c50bdf21b1072a2c799

Fox, G.A.; Sabbagh, G.J.; Searcy, S.W.; Yang, C. An automated soil line identification routine for remotely sensed images. Soil Sci. Soc. Am. J. 2004, 68, 1326–1331.

Huber, P. “Robust estimation of location parameter” Annals of Mathematical Statistics, 1964

McDonald, Robert I. et al. “Water on an Urban Planet: Urbanization and the Reach of Urban Water Infrastructure.” Global Environmental Change 27.1 (2014): 96–105. Web.

Mcdougall, Robert, et al. “Small-Scale Urban Agriculture Results in High Yields but Requires Judicious Management of Inputs to Achieve Sustainability.” *Proceedings of the National Academy of Sciences*, vol. 116, no. 1, 2018, pp. 129–134., doi:10.1073/pnas.1809707115.

McSweeney, Robert, and Katerina Michaelides. “‘Desertification’ and the Role of Climate Change.” CarbonBrief, 8 June 2019.

Mougeot L.J.A, (2000) Urban agriculture: Definition, presence, potentials and risks. Growing Cities, Growing Food: Urban Agriculture on the Policy Agenda, Cities Feeding People Series, vol 31, pp 1–42.

NASA. "Landsat Data Continuity Mission Brochure" 2010. Web.

Sazib, Nazmus, et al. “Leveraging the Google Earth Engine for Drought Assessment Using Global Soil Moisture Data.” Remote Sensing, vol. 10, no. 8, 2018, p. 1265., doi:10.3390/rs10081265.

Schreck, Brownstein Hyatt Farber. “Law Water Toward Sustainable Growth in Arid Climates : Requiring Developers to Show Water Supplies Are Adequate.” 100.8 (2017): 16–19. Print.

Shelestov, Andrii, et al. “Exploring Google Earth Engine Platform for Big Data Processing: Classification of Multi-Temporal Satellite Imagery for Crop Mapping .” Frontiers in Earth Science, 2017, doi:10.3389/feart.2017.00017.

Torres-Rua, A. (2018). Hydroshare-GoogleEarthEngine, HydroShare, http://www.hydroshare.org/resource/87a6e0a657814f6ea0b5cebd256cc3da

UNDESA. “World Urbanization Prospects: The 2011 Revision.” Presenta-tion at the Center for Strategic and … (2012): 318. Web.

Vapnik, V. “The nature of statistical learning theory,” Springer, New York (1995).

Xu, Dandan, and Xulin Guo. “A Study of Soil Line Simulation from Landsat Images in Mixed Grassland.” Remote Sensing, vol. 5, no. 9, 2013, pp. 4533–4550., doi:10.3390/rs5094533.

Xue, Jinru, and Baofeng Su. “Significant Remote Sensing Vegetation Indices: A Review of Developments and Applications.” *Journal of Sensors*, vol. 2017, 2017, pp. 1–17., doi:10.1155/2017/1353691.

Zou, Xiaochen, and Matti Mõttus. “Sensitivity of Common Vegetation Indices to the Canopy Structure of Field Crops.” *Remote Sensing*, vol. 9, no. 10, 2017, p. 994., doi:10.3390/rs9100994.

BIOGRAPHY

Paul Consalvo was born in Tampa, Florida and grew up in both Tampa and New York, New York. Paul's major is Civil Engineering and his minor is Computer Science. Originally, Paul wanted to study music, but his plans changed suddenly and forced him to "get good" regarding math. He accomplished this quite well, securing a spot on the Dean's List for eight semesters and being an invaluable member of his research teams and the Utah Department of Transportation Traffic and Safety team.Paul is a member of the Undergraduate Research Fellowship, USU Honors Program, and Community engaged Scholars Program, and he is graduating with transcript designations from all three programs. Paul is a recipient of multiple Honors scholarships, the USU Presidential Scholarship, and a National Conference for Undergraduate Research Scholarship. He is also a captain for the USU Concrete Canoe Team, a Undergraduate Research Fellowship Ambassador, and was the Sustainability Resident Assistant for the USU Student Living Center. After leaving Utah, Paul will gallivant around Utah and Idaho before beginning his job as a Transportation Analyst with Kittelson & Associates in Tallahassee, Florida. Not knowing what to originally expect, Paul found his time in Utah was necessary in forming him personally and academically, and thinks some traits of the people in Utah will lead him back one day.