Analysis of the effect of different irrigation and fertilization strategies in Kentucky bluegrass

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INTRODUCTION

Rapid population growth, economic development, and climate change are all contributing to increased demands on global water resources. Water stress is already apparent in arid and densely populated regions world-wide and projections show that water scarcity shows a pattern of pandemic increase in the years to come. The areas at most risk are urban areas, which are projected to be the location of much of the world’s population increase1,2. Because agriculture is estimated to be responsible for nearly 90% of groundwater consumption globally3, it stands to reason that water conservation has been emphasized in agricultural systems. However, locally available water in urban locations is also at risk. There is significant potential for water conservation within urban landscapes, particularly in arid and semi-arid environments4.

Urban water protection efforts have identified residential and commercial landscapes as one of the largest sources of conservation potential. These landscapes are estimated to consume 40-70% of all municipal water.5 Covering approximately 50 million acres in the US, turfgrass is the most common landscape feature in most urban landscapes and consumes the majority of water in landscapes. Endter-Wada, et al., performed research on urban landscape water consumption in Utah, where they determined that lawns were typically overwatered. The most common reason for overwatering is automatic, timer-run sprinkler systems. These systems water lawns at designated times regardless of actual water needs. Due to this and other factors, 31.3% of residential and 64.8% of corporate sites were practicing wasteful landscape watering6. Although community resource management strategies have been shown to be effective in reducing urban water consumption2,6, more can be done as landscape managers have a better understanding of optimizing water application.

The importance of nutrient management and its relationship to turf water use and drought tolerance is often overlooked. For example, application of excessive nitrogen fertilizer is common in landscape turf settings. Excess nitrogen increases rates of growth and water use and simultaneously reduces root development7, both of which make turf more vulnerable to drought. However, nutrient deficiencies can also be problematic when drought occurs because plants are already experiencing abiotic stress and are less able to tolerate drought conditions. It is important for turf managers to find optimal nitrogen amounts in order to optimize water use. This can be done by carefully regulating plant health. There is current interest in improving the combined management of water and nutrients in turfgrass. One approach being evaluated is to employ soil or remote sensors to fertilization and watering decisions.

Remote sensing technologies have been available for decades, but have not been applied to turfgrass on a large scale. They have proven to be incredibly valuable in other cropping systems. Measuring the temperature of the turf canopy with an infrared thermometer is one remote sensing approach of interest. The first infrared thermometer devices were developed in the 1960s and was discovered to work well for assessing water stress, because canopy temperature increase as plant available water declines. This is because transpiration has a cooling affect, so a decline in transpiration leads to an increase in temperature. A method developed in the 1980s compares measured canopy temperatures with well-watered and non-transpiring baselines to produce a measurement called the Crop Water Stress Index (CWSI)8. One problem with use of CWSI alone to optimize water application is that some nutrient deficiencies may have a confounding affect. This was demonstrated by Carroll, et al., in maize8. However, some of these can be accounted for by including spectral reflectance sensors. These measure the Normalized Difference Vegetation Index (NDVI) of plant canopies and can be used to assess green biomass or nitrogen content9.

In one of the first studies using remote sensing in turfgrass, Taghvaeian et al.10 used hand-held, multi-spectral radiometers to determine which species of grass were most tolerant to water stress. Information from the radiometers was sent to a data-logger controller, which stored information for analyses. One downside to this system is that measurements must be taken within two hours of solar noon on cloud-free days, and measurements took an average of 37 minutes on each study day.

The Brigham Young University Turfgrass research program is seeking to optimize water and nitrogen supply. As part of this goal, they would like to evaluate the potential application of soil water sensors and remote canopy sensors to improve irrigation and fertilization decisions. Construction of a turf irrigation research facility was initiated outside of the BYU research greenhouse in the fall of 2016 and Kentucky bluegrass (*Poa pratensis)* was established in the summer of 2017. The facility consists of 27 individual research plots (3.4 m x 3.4 m), divided in a randomized, complete block design among three irrigation zone treatments. Irrigation treatments are deficient, optimum, and excessive. Within each irrigation treatment, there are three nitrogen levels, each replicated three times. Nitrogen fertilizer treatments are deficient, optimum, and excessive. In collaboration with Decagon Devices, water content sensors, water potential sensors, spectral reflectance sensors, and infrared radiometers monitor the plots and report to data-loggers in the field. These sensors take automatic measurements hourly and require much less user interaction than those used in previous studies. If they prove effective, they are in a price range that would make them accessible to businesses and parks, resulting in more efficient watering in urban landscapes. During a three-week period from 9-23-17 to 10-16-17, the nitrogen and fertilizer treatments were implemented and sensor activity logged. Our objectives are to create a data pipeline that will allow the user to combine all sensor data, visualize soil and plant conditions over time, identify periods where stress occurred, generate descriptive statistics to compare experimental treatments, and provide a Docker container11 that will make it possible to recreate our analysis on future data-logger datasets.

METHODS

*Data Generation*

The Brigham Young University Turfgrass research program provided data from 13 Decagon data-loggers. Each data-logger supports input from up to five sensors, but not all ports were utilized on all loggers. Rows 4, 5, and 6 had two loggers—each with full port utilization, but the rear bank of sensors reported data only for the plot in the third column. Data from the rear bank had to be combined with third-column plot data from the forward bank on these rows.

Both the GS3 and MPS6 sensors report soil temperature. With the additional sensors in the third-column plot (one each at 64cm, 150cm, and 300cm), there is both a GS3 and MPS6 sensor at 150cm and 300cm and just an MPS6 at 64cm on the rear bank, and a GS3 at 64cm on the forward bank. We calculated the average of the two soil temperature measurements at each sensor depth.

There is also the issue of missing observations from row 1 and row 7. For some reason, the data-loggers missed two observations completely: 5/10/2017 1700 (row 1) and 5/24/2017 1100 (row 7). Considering the total number of observations (169k), we deemed this an acceptable error rate (0.0012%). However, despite the low error rate, given that there are only 24 observations in a day, this throws off data for the entire row for most of the observation timeframe (including the drydown period).

*Data Tidying and Preparation*

The .xls data files output by the Decagon server were not properly initialized—the file header was missing data, and it was necessary to manually open and save each file in Excel in order to reinitialize the metadata. Simply saving the file with no changes is sufficient to fix the header. Future work would include working with Decagon to fix the issues in file generation.

To reinitialize the files, we used Microsoft Excel for Mac (v15.27). After reinitializing the file metadata, data retrieval and processing was done in a Jupyter Notebook running jupyter\_core 4.3.0 (on Python v3.6.2). The numpy (v1.13.0) and pandas (v0.20.2) libraries were also used. We exported the Jupyter Notebook to a single python script that can be run from the command line (such as bash or zsh).

After initialization, starting with the file generated by the data-logger on the front of the first row, each file was read in as a pandas dataframe. For each row, sensor data for individual plots was sliced into separate frames. For rows 4, 5, and 6, rear-bank plot data (for the third column) was sliced and merged with third-column plot data from the forward sensor bank. For all rows, data from each plot was stacked into a single frame. Finally, each frame corresponding to each row was stacked and output to a tab-delimited file (allrows.tsv) with nulls as “N/A” for further processing by R. One of the data-logger files logged irrigation flow for all of the plots (first row rear sensor bank), so it was not included in the main dataframe; data from this file was read into a separate frame so it can be merged with the final frame later.

*Adjusting for Missing Data*

To account for the missing observations, we simply checked during the initial processing steps and inserted zero data. This re-aligns the errant logs so that observations can be compared chronologically. Future work would include modifying the code to handle missing observations (wherever they might occur) by alerting the user and/or automatically inserting zero data.

*Docker Setup*

To facilitate reproducibility, we created a Docker container based on the Python3 image using Docker version 17.12.0-ce. To use the Docker container, download the most-recent recent version of Docker. Make sure the daemon is running. We recommend going through at least the first two steps of the Get Started guide. Then, clone the repository and switch to the root folder. Make two directories: “data” and “results,” then copy the (re-initialized) data files into the first folder (/data). Now run the run\_docker.sh script. This will build the container, run an image based on the container, then copy the output file to the results directory.

By default, the script will only create the final file, but the boolean outputIntermediateFiles in process\_input.py (line 22) can be set to “True” and intermediate files will be created in the /data folder. These files will need to be copied from the image manually.

*Figure Design*

R and RStudio will be used to analyze trends in the data from the three-week period of interest. The readr and dplyr packages will be used to read the tidied data into dataframes, then select only rows associated with the study period. The ggplot2 package will be used to design figures demonstrating relationships between treatments and plant stress. We will also use R to employ a one-way ANOVA test, determining the significance of the relationship between available water content and nitrogen treatments. The resulting code will be added to the Docker container for analyses of future studies.

RESULTS

Although the timing of this experiment coincided with precipitation that may have interfered with irrigation-related results, we hope we will still be able to identify trends in the data. It will be particularly interesting to visualize the effect of different nitrogen treatments at deficient irrigation levels. We hope to provide excellent analysis tools in the Docker container system that can easily applied to future duplications of this study. Using the ggplot2 package in R, we propose the following figures:

1. We will provide a diagram of the study site, including treatments applied to each plot, sensor locations, and data-logger locations.
2. Plots 43, 53, and 63 are all provided with optimum nitrogen fertilizer, but each represents a different irrigation treatment (full, high, and low, respectively). They each have water potential sensors at 6” and 12” beneath the soil surface. These give values (in kPA) for water that is available to the plant. This chart will help readers to visualize the three water treatments in optimal nitrogen conditions over time. Separate charts may be necessary for each depth.
3. Volumetric water content data is available from all 27 plots. This data will be used to plot the total soil water content by water treatment for each nitrogen treatment. Separate graphs will be made for each water treatment. Here, we expect to see available water decrease (particularly in low irrigation treatment plots) in plots that have been treated with excessive nitrogen.
4. Three charts (one for each irrigation treatment) will be developed to show the change in NDVI over time between nitrogen treatments. Here, we expect to see NDVI values decrease over time in nitrogen deficient plots, and more so in plots that are also water stressed.
5. Line charts will be developed to show the change in canopy temperature over time. Because increased canopy temperature is associated with water stress, the most interesting treatments to observe will be the high nitrogen treatments with low water supply. These should show more stress than low water plots with optimal or deficient nitrogen application.
6. Finally, we will provide a schematic to demonstrate the process taken to tidy, combine, analyze, and containerize the data.

For the Milestone Results assignment, we will provide a completed schematic and the first line chart described above.

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