Using Smart Irrigation Technologies to Advance Urban Landscape Irrigation in Inland Southern California

Deliverable #5: Final Report

Agreement No. 180897

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1. Introduction:

Statistics indicate California's population increased to nearly 40 million in 2016 and projections by the California Department of Finance indicate an increase of more than 45 and 50 million by 2035 and 2060. The largest increases in population has continued in big cities where efficient landscape irrigation management has become critical, emphasizing the importance of this project. Typically, more than half of household water is used outdoors, and irrigated landscape is the main outdoor user of residential water. Landscape water use in summer months can account for up to 90% of total municipal water use. Literature indicates more than half of the applied water for landscape irrigation could be wasted due to over irrigation, inefficient irrigation and broken or poorly maintained irrigation systems. Significant reductions in applied irrigation water (about 40-80%) have been reported as a result of implementing smart irrigation technologies for landscape irrigation management in humid regions in Florida and North Carolina. This project aimed to develop efficient landscape irrigation management strategies using smart irrigation technologies in inland Southern California.

2. Study site:

In late 2018, two adjacent research sites were established at the University of California, Riverside Agricultural Experiment Station in Riverside, California, consisting of a total of 144 landscape irrigation plots (10 feet × 10 feet). Each plot was equipped with four quarter-circle (pop-up heads) sprinklers, all four connected to a solenoid valve allowing independent irrigation control for each plot. To eliminate the plot edge effect and avoid interference between adjacent plots, adequate borders (~ 4 feet) were considered.

3. Plant species

Twelve different landscape species that are commonly used or are alternative species that have the potential for urban settings in inland Southern California were selected for this study. The list of twelve species is presented in Table 1. The plots were planted in early 2019 and were under full irrigation for root establishment for several months afterward. A relatively cold and wet winter and spring in Riverside forced us to delay planting and also slowed down the growth of the plants.

The experimental plots were frequently hand-weeded to keep them weed-free. Also, plant species were pruned from top and side to prevent them to grow higher than the sprinkler heads (12 in) and to make sure the growth was always within the dimension of the plot (10x10-ft). This practice helps to confirm there is no interference in the irrigation application and all plants are getting the amount of water we wanted to apply. The alleyways between the plots were sprayed frequently to keep them weed-free.

Figure 1. Aerial view of the landscape irrigation project at UC Riverside.

Table 1. List of landscape species (aka groundcover) used in the irrigation study

Species number	Scientific name	Common name
1	*Eriogonum fasciculatum*	Buckwheat
2	*Frankenia thymifolia*	Sea heath
3	*Lantana montevidensis*	Lantana
4	*Trachelospermum jasminoides*	Jasmine
5	*Lonicera japonica*	Honeysuckle
6	*Delosperma cooperi*	Ice-plant
7	*Ruschia lineolata*	Ice-plant
8	*Rhagodia spinescens*	Creeping Australian saltbush
9	*Rosmarinus officinalis*	Rosemary
10	*Eremphila glabra*	Gold Emu Bush
11	*Baccharis x 'Starn' Thompson*	Coyote bush
12	*Oenothera stubbei*	Saltillo evening

3. Irrigation Experiment

A Weathermatic smart ET-based irrigation controller was installed and wired to all the solenoid valves for autonomous irrigation scheduling throughout the experiment. In addition, a Weathermatic flow meter, and weather station were installed and attached to the smart controller.

Later during the study, the Weathermatic flow meter was replaced with a Badger flowmeter to precisely monitor the applied water at the plot level. In September 2019, four irrigation treatments were set to schedule autonomously by the smart controllers to determine the impact of irrigation frequency (i.e., 7, 5, 4, and 3 days per week watering days) on growth and health of the landscape species. The treatments were replicated three times in a randomized complete block design. The irrigation amount of 80%ET*ref* was identically applied among species.

4. Data collection and analysis

A total of 296 Acclima true Time-Domain Reflectometry (TDR-315L) soil moisture sensors were installed at the center of 18 plots. The sensors were installed at eight depths up to 5 feet deep to monitor soil water status within and below the active root zone of the plants. A total of 36 junction boxed and 3 data logger/multiplexer enclosures with telemetry capability were prepared to continuously collect soil moisture data throughout the experiment.

Figure *2*. TDR sensors installation steps at different depths.

We continuously monitored the effect of irrigation on the growth and health of the plant species by measuring the NDVI values (Normalized Difference Vegetation Index, a measure of plant greenness and health) for all the twelve species. NDVI was measured using a handheld sensor

(GreenSeeker, Trimble Inc., CA) and via a drone (3DR Solo) equipped with Micasense Rededge multispectral camera.

5. Results

5.1 Performance of the smart controller and overall irrigation application

On average and for the entire duration of the irrigation study combined, we observed only a 3% difference between the water applied autonomously by the smart ET based controllers versus target water application based on independent ET data collected from the nearby CIMIS station. This finding is promising since the smart controllers used in this study only measure on-site temperature data to calculate the ET using the Hargreaves equation.

A common practice in urban irrigation projects is to estimate the precipitation rate of the system based on the catch-can test. We initially followed this procedure and a precipitation rate of 0.67 in/hr was estimated for the system. Later, when we used flowmeter data we obtained a much higher precipitation rate of 1.12 in/hr. After installing and calibrating the flowmeter the precipitation rate was adjusted to 0.96 in/hr. These findings suggest that flow and precipitation rates estimated using a catch can test or uncalibrated flow meter may not be reliable and therefore, should not be used for programming the smart controllers. The post-processing of our data shows that instead of 80%, only 61% ET_{ref} was applied throughout the irrigation study. However, this does not affect the results as 61% was used for all the species and we focused mainly on the irrigation frequency in this study. In a subsequent study, we will impose multiple deficit irrigation treatments on these plots to develop water conservation strategies and determine the minimum water requirement for each species.

5.1. Monitoring plant growth and health

Table 2 shows the effect of irrigation, plant species, and their interaction on the NDVI of different plant species. The NDVI was found significantly different between the species as shown in table 2. The interaction effect of irrigation and species was not found to be statistically significant. The effect of irrigation frequency was statistically significant only in one event (25th Sept. 2019; figure 3); otherwise, irrigation frequency did not affect the landscape plant health and growth as quantified by NDVI values. This result suggests that when the irrigation application is efficiently regulated by a smart controller, restricting watering days to only multiple days per week (a strategy often imposed by municipalities during the droughts) is not necessary since it does not result in saving water or higher quality of landscape species. More studies are needed to confirm this finding.

Table 2. Effect of irrigation, plant species and their interaction on NDVI collected using drone and handheld sensors.

Methods	**Date**	***p*-values**		
		Irrigation	**Species**	**Irrigation × Species**
Drone	16-Jul-19	0.8825	<0.0001	0.6097
	1-Oct-19	0.7454	<0.0001	0.7051
	8-Oct-19	0.7094	<0.0001	0.9172
Handheld Sensor	16-Jul-19	0.1788	<0.0001	0.9763
	25-Sep-19	0.0188	<0.0001	0.9329
	7-Oct-19	0.8616	<0.0001	0.9920

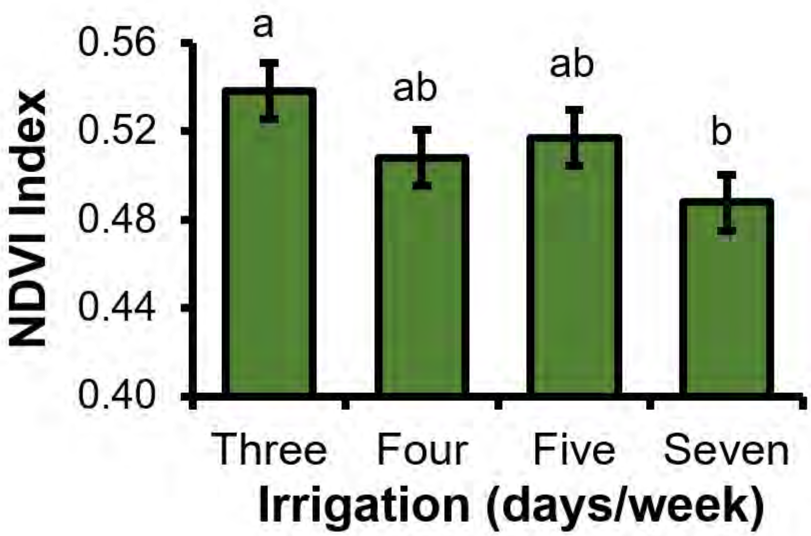


Figure *3*. Effect of irrigation frequencies in the NDVI (Sept. 25, 2019; handheld sensor). Different letter assignments are significantly different at p<0.05.

The NDVI collected from handheld and aerial remote sensing showed that the species #5 (i.e., honeysuckle) performed well, yielding very high NDVI values across all measurements (figure 4). On the other hand, the plant species #2 (i.e., sea heath) had the lowest NDVI values across all the measurement dates (figure 4). These findings are further supported by aerial images taken from the drone (figure 5) wherein greater NDVI is attributed to higher coverage and healthier plants.

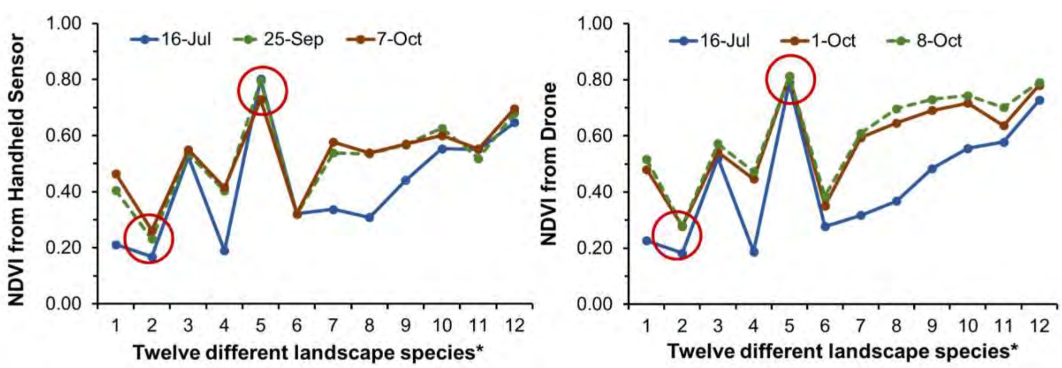


Figure 4. NDVI distribution of twelve different landscape species as measured by handheld sensor (left) and drone imaging (right). *Species 1-12 in the x-axis are listed in table 1.

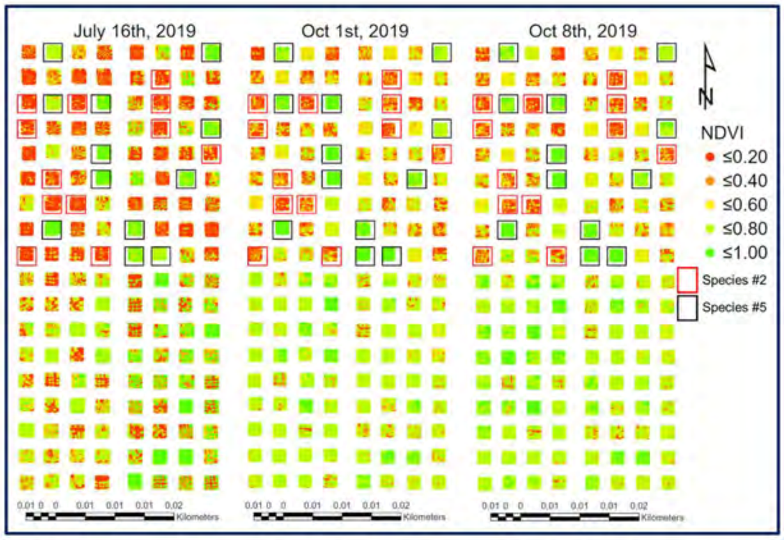


Figure 5. Field map captured by the drone showing normalized difference vegetation index (NDVI) at different periods of time.

We found a good agreement (i.e., strong correlations: $0.81<r^2<0.97$) between the NDVI data collected using the handheld sensor versus drone images. This finding shows that aerial remote sensing using a drone can be useful in monitoring landscape plant health and detecting drought injuries and can be a replacement for more labor-intensive and time-consuming handheld sensors.

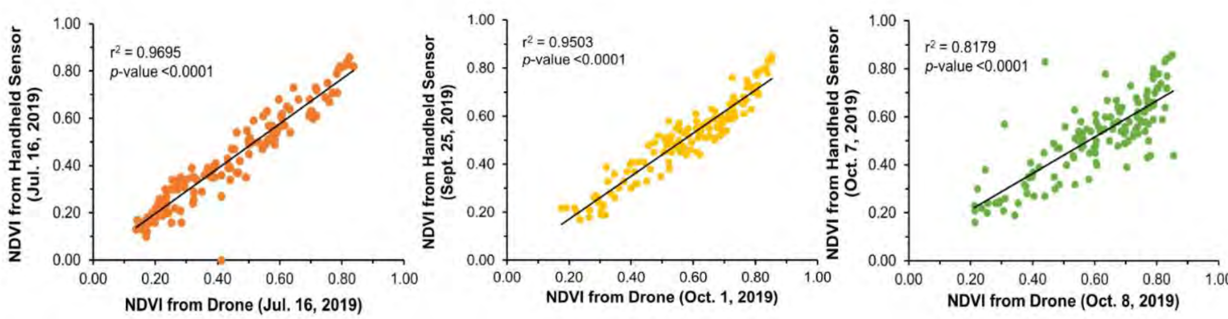


Figure 6. Correlation between NDVI data collected from drone and handheld sensors

Soil moisture data obtained from the TDR sensors for each of the plant species is presented below (figure 7). The primary y-axis depicts volumetric water content (VWC) in percentage, the secondary y-axis shows precipitation and irrigation in inches, and the x-axis is the date when the varying rates of irrigation frequency were applied. Across the species, the highest increase in the soil moisture occurred due to the heavy precipitations, while typically only top sensors show fluctuations associated with irrigation applications. This indicates the importance of managing soil moisture to a lower level than its field capacity in rainy seasons so the rainfall could penetrate and be stored in the soil profile. As irrigation season progressed, more fluctuations become evident in intermediate soil moisture sensors, which indicates root growth and water uptake from deeper layers.

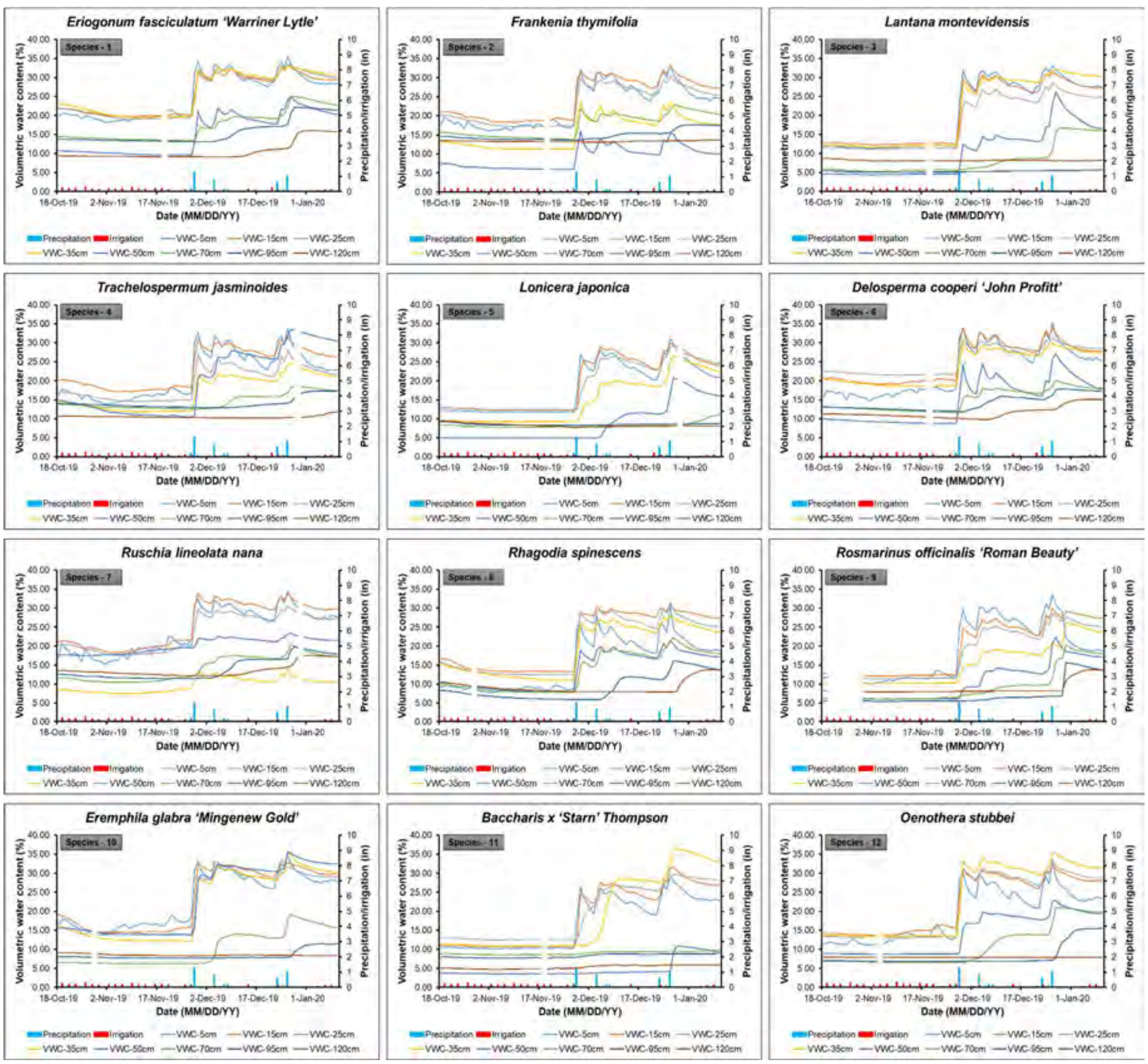
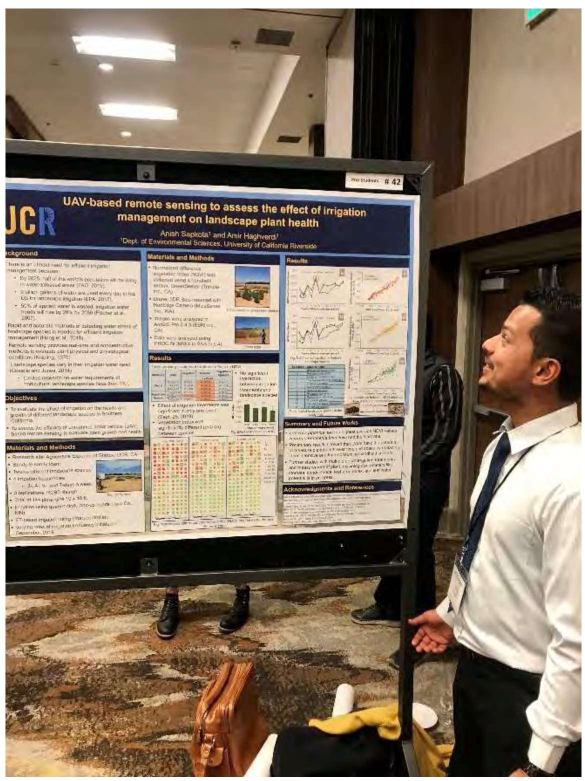


Figure 7. Volumetric water content measured by TDR sensors installed at different depth in the study site, and the precipitation and rainfall event during the study period.

Extra Photos:

Ph.D. students Anish Sapkota and Amninder Singh calibrating the flowmeters for accurate measurement of applied water.

Ph.D. student Anish Sapkota collecting NDVI data using a handheld sensor.



Ph.D. student Anish Sapkota presenting a poster at California Plant and Soil Conference, held at Fresno Doubletree Hotel, Fresno, CA on Feb 4-5, 2020.