Spatial Analysis of Soil Moisture and Turfgrass Health to Determine Zones for Spatially Variable Irrigation Management

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Abstract

Irrigated turfgrass is a major crop in urban areas in the western United States which is currently experiencing severe drought. A large proportion of irrigation water is wasted using conventional sprinkler systems. Smart Sprinkler systems currently reduce temporal mis-applications, but the most accurate and cost-effective variables to determine spatial zones for application need to be explored further. This research uses data from ground and drone surveys of two large sports fields to determine spatial irrigation zones using principal components analysis and k-means. Zones are developed using all field measurements, soil moisture measurements and NDVI measurements and assessed. The errors associated with uniform irrigation and different configurations of spatial zones are assessed to determine potential improvements in irrigation efficiency afforded by spatial irrigation zones. A determination is also made as to whether the spatial zones can be temporally static or need to be re-determined periodically. Analysis suggests that zones based on spatial soil moisture surveys are better than those based on NDVI. Also, ideally zones should be re-evaluated before each irrigation. However, a less labor-intensive solution is to determine temporally static zones based on the similarities in or average patterns of soil moisture from several surveys.

Keywords

Turfgrass, Irrigation, management zones, soil moisture, NDVI

Introduction

The Southwest region of the USA has seen the greatest expansion in urban development in recent years and this has put pressure on the limited freshwater supply (Anderson and Woosley, 2005). This has been exacerbated by recent drought. Currently, >30% of the West is experiencing "extreme" or "exceptional" drought (https://droughtmonitor.unl.edu/). The conversion of land to urban areas has meant that more acres of irrigated turfgrass (>40 million) are now grown in the USA than irrigated corn, wheat and fruit trees combined (Milesi et al., 2005). It has been estimated that about 60% of household water is used to irrigate lawns (EPA, 2017) and this proportion is likely to be higher for institutions that do not have residential functions. It has also been estimated that as much as 50% of turfgrass irrigation water is wasted (EPA, 2017) due to temporal and spatial mis-applications. The US EPA has implemented the "WaterSense" program which addresses a temporal mis-application issue as the irrigation controllers tailor watering schedules to local weather conditions. This modification alone can reduce irrigation water use by 15% (EPA, 2017). However, the EPA is considering developing irrigation scheduling that is controlled by soil moisture sensors (EPA, 2017) like those being used with agricultural variable rate irrigation systems like that of Liakos and Vellidis, (2021). However, turfgrass does not produce a crop that can be sold to offset the cost of sensors. Also, the technology for precise urban irrigation has been largely lacking due to traditional, inefficient irrigation systems and the cost/complexity of sensors.

Recently, affordable technologies have emerged to help solve the urban water crisis. These include sprinkler heads using "valve in sprinkler head technology" (such as those produced by Hunter, Rainbird, and Toro) which allow each sprinkler head to be operated independently, rather than via the standard practice of blanket application rates by zone with rates being determined by the driest part of the zone. Many residential customers turn on their sprinkler systems to water every other day for 20 or 30 minutes in every zone at the beginning of the season and never adjust those levels until they turn the sprinklers off at the end of the season. Clearly, a more informed irrigation schedule and zoning is needed. New generation soil moisture tension sensors improve accuracy and the simplicity of use of soil moisture sensors and turfgrass can be monitored using drones equipped with cameras that record wavelengths of light that are sensitive to plant health. Finally, smart controllers allow the incorporation of multiple information layers, with weather data, to precisely control irrigation. The main concerns in determining spatial zones for turfgrass irrigation revolve around being able to determine the zones in cost-effective ways, especially if they need periodically or routinely reassessing, or re-evaluation before each irrigation event. This paper investigates the effectiveness of different variables for determining spatial zones for driving soil moisture applications for two general sports fields on Brigham Young University (BYU) Campus. Developing spatial zones should be more feasible economically for large institutions in the first instance where irrigation forms a larger proportion of water bills, but it is hoped that methods developed here may eventually be transferred to the residential turfgrass irrigation sector with a change in the scale of inquiry, so the cost of the equipment needed to make various measurements to base zones on is considered here also.

Methods

Field and Drone Surveys

Two general sports fields growing Kentucky bluegrass turf on BYU campus were the field sites for this work. Harmon field has a gentle N-S running slope and the field dimensions are approximately 150 m (N-S) by 115 m (E-W) Figure 1c. Temple field has a slightly steeper NE-SW running slope and the field dimensions are approximately 200 m (NW-SE) by 150 m (NE-SW) Figure 2c.

Harmon field has traditional sprinkler zones installed which generally run E-W across the field in parallel with the elevation (Figure 1c). However, at the edges of the field, zones run N-S counter to the elevation patterns. In the 2021 irrigation season, field managers were applying 30% less water to the 3 zones at the bottom of the slope. The NRCS web soil survey website: https://websoilsurvey.sc.egov.usda.gov/App/WebSoilSurvey.aspx classified the soil in the Harmon field as 3 types: Taylorsville silty clay loam with 1 to 3 percent slopes, Pleasant Grove gravelly loam with 3 to 6 percent slopes and the Sterling gravelly fine sandy loam with 1 to 3 percent slopes covering 91.5, 5.5 and 3% of the field area, respectively (see Figure 4d). The two less prevalent soil types were found only in the NW and SE corners of the field. A survey of top-soil texture along two N-S running transects towards the center of the field showed a consistent sandy loam texture rather than silty clay loam. Silt content was, however, shown to be greatest in the center and eastern portions of the field where the Taylorsville silty clay loam was supposed to dominate.

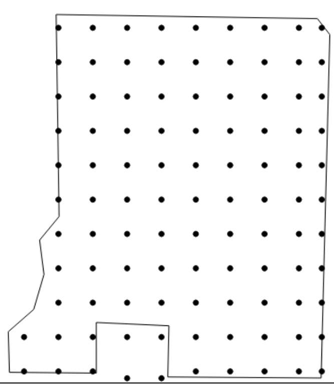
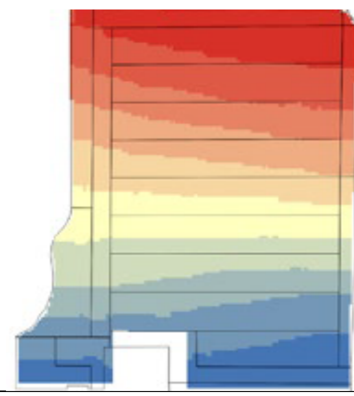
(a) 15 m Grid, Ground Survey Points	(b) September 2020 RGB Drone image	(c) Sprinkler zones (black lines) and Elevation from 1387 m (blue) to 1392 m (red)
		

Figure 1. Maps of Harmon field showing (a) Ground survey Grid, (b) September 2020 RGB Drone image and (c) Sprinkler zones in relation to elevation (m)

Temple field has new valve-in-head sprinklers where each sprinkler head can form its own zone. Figure 2c shows the area covered by each sprinkler head as a black circle with radius of approximately 27 m. The sprinkler heads are spaced at 20 m so that there is overlap (Figure 6f) between the areas watered by each sprinkler head. The sprinkler heads in temple field were installed in NW-SE running lines that are consistent with changes in elevation running across the slope (Figure 2c). In the 2021 irrigation season field managers were applying 30% less water to the 3 rows of sprinkler heads at the bottom of the slope. The NRCS web soil survey classified the soil in the Temple field as all of one type, the Pleasant Grove gravelly loam with 3 to 6 percent slopes, however, a survey of top-soil texture along two NW-SE running transects towards the center of the field showed soil textures varying between Clay loam, Loam and Sandy Loam. Also, some of the patterns of soil texture seem to account for non-typical patterns of soil moisture with some clay soils and even gleying observed at the top of the slope and sandier soils near the bottom of the slope. Most evident in this field was sudden, unpredictable changes in soil texture. This may have something to do with two pipelines that have been installed under this field in recent years. Construction workers likely re-filled the areas above the pipeline with sand rather than soil. Also, this field is part of an alluvial fan which could also account for the sudden changes in soil particle size within the field.

Ground surveys of both fields were performed on a 15 m grid (Figures 1a and 2a). Harmon field was sampled in September 2020 (S20), March 2021 (M21), twice in August 2021($A21_{a+b}$) and again in September 2021 (S21). Temple field was only sampled once in July 2021 (J21). Table 1 summarizes the observations that were made during each survey. Handheld sensors such as a Delta T theta probe, Trimble Greenseeker NDVI sensor and fieldscout greenindex+ Turf app were used to measure soil volumetric water content (VWC) and normalized difference vegetation index

(NDVI), the greenness of grass, or grass health on 15 m grids across both fields. Delta T theta probes currently cost about \$1500, Trimble Greenseeker handheld devices cost about \$650 and the Fieldscout GreenIndex+ Turf app and board costs \$100. There was no equipment cost for estimating % dead or discolored grass and the dry/wet soil indicator.

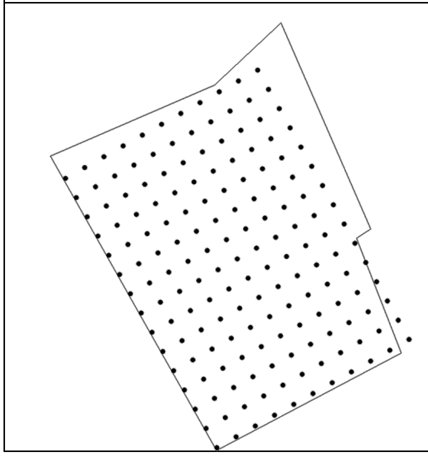
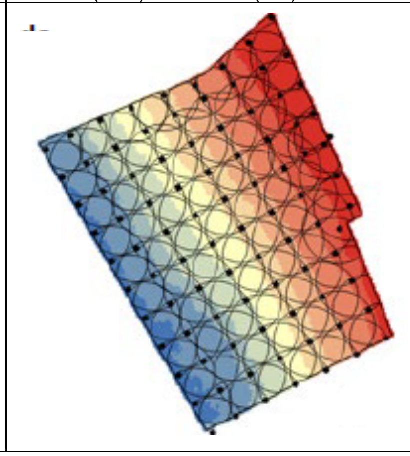
(a) 15 m Grid, Ground Survey Points	(b) July 2021 RGB Drone image	(c) Sprinkler zones (black lines), sprinkler heads (black dots) and elevation from 1443m (blue) to 1463 m (red)
		

Figure 2. Maps of Temple field showing (a) ground survey grid, (b) July 2021 RGB drone image and (c) sprinkler heads and zones in relation to elevation (m)

Table 1. Variables measured, instruments used and dates sampled for field and drone surveys of Harmon and Temple fields

Variable	Method or Instrument used	Dates sampled
% dead or discolored grass	Estimates using quadrats	S20, M21, A21a, S21
Soil Dry/Wet (0/1) Indicator	Touch	S20, M21, A21a+b, S21
NDVI meter	Trimble Greenseeker handheld	S20, M21, A21a+b, S21, J21
NDVI App	Fieldscout GreenIndex+ Turf app and board	A21a+b, S21, J21
Top-soil VWC (%)	Delta T theta probe	S20, M21, A21a+b, S21, J21
Elevation (m) (6 cm pixels) and Slope, Aspect, TWI	Drone DSM processed in Drone Deploy, Pix4D then SAGA GIS	S20, M21, A21, J21
R, G, B, NIR, NDVI, VARI (6 cm pixels)	Drone images processed in Drone Deploy and Pix4D	S20, M21, A21, J21

A DJI Phantom 4 drone equipped with a 12mp (4000 x 3000) camera and a Sentera Single Sensor NDVI was used to capture RGB and NDVI imagery and a digital surface model (DSM) of the field with a pixel size of 6 cm (Table 1). Visual Atmospheric Resistance Index (VARI) data, a vegetation index which uses only the RGB wavelengths was also calculated from this drone imagery as were several derived topographic attributes from the DSM (Table 1). The drone and camera equipment costs about \$3000 as well as a subscription to the data/image processing website. Drone survey also requires a drone pilot license to fly, and in urban areas, health and safety forms must be submitted and approved before each flight.

Statistical Methods

Ground survey data were kriged to a 1 m grid (Figure 3a) and drone data were resampled to a 1 m grid to aid in the speed of data processing. Pearson correlations and the bi-variate local Moran's I (LMI) were used to investigate the consistency of patterns between soil moisture and grass health from different surveys.

Within precision agriculture, a common approach to defining management zones is to use several dense, inexpensive sensed variables that are related to the variable to be managed and then determine zones from these data using principal components analysis (PCA) and K-means classification. K-means was used to classify individual variables and composite variables from principal components analysis (PCA) into different numbers of zones. Where there was the greatest break of slope in a scree plot (Figure 3b) was used as the optimum number of zones. Zones were then defined using shape files (Figure 3c, black lines).

Using existing zones (Figures 1c and 2c) and the optimal zones determined using individual variables and combinations of variables, average VWC per zone and per field were calculated from the 1 m kriged VWC data. The errors associated with irrigating to field and zone average VWC were calculated and compared.

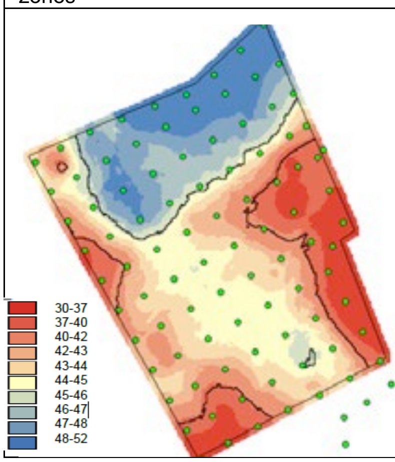
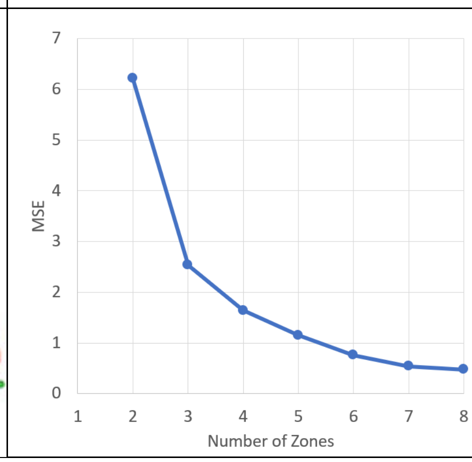
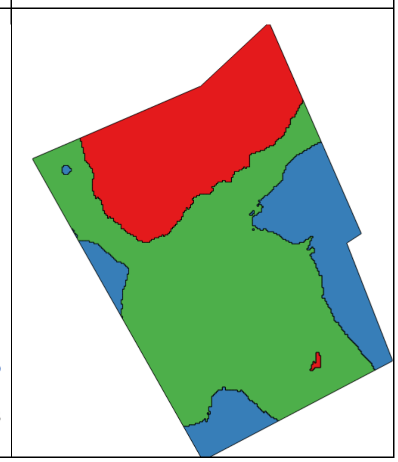
(a) Kriged VWC (%) with sprinkler heads (green dots) and proposed VWC zones	(b) Scree plot to determine the optimal number of zones	(c) 3 optimal zones based on VWC
		

Figure 3. Maps and graph of Temple field showing (a) kriged VWC (%) within the field, (b) Scree plot for determining optimal number of zones and (c) location of 3 optimal zones based on VWC

Results and Discussion

Figure 4 shows that there are similarities in the patterns shown in the maps produced from interpolated ground survey values and these variables had moderate correlations with each other (+/- 0.3-0.7). For example, there are similarities in the location of the areas with a high percentage of dead or discolored grass and the area with dry soil from the S20 and S21 surveys, respectively (compare Figures 4a and b). There are also similarities between the patterns in these maps and those shown for NDVI meter (S20), % VWC (S21), NDVI App (S21) and drone NDVI (S20) (Figures 4 c-f). The similarities in the patterns of the variables that do not need expensive equipment to measure them (Figure 4a, b, and e) to the patterns of the other variables shows promise for the potential to transfer the approaches developed here to the residential context. Each of the variables shown in Figure 4 seems to show a dominant E-W pattern with high values of VWC, NDVI and low values for deadgrass in the east of the field and the reverse in the west of the field. These patterns show consistency with the patterns of degree of slope Figure 4g. There is also a slight N-S pattern for the dry/wet indicator and the % VWC with the southern end of the field, which is lower down the slope, tending to be a little wetter than the northern end of the field.

This is logical given the direction of the slope of the field and the consistency in soil texture within the field, but at first assessment of the field, one would expect this to be the dominant feature of variation in the field rather than the E-W variation.

The bi-variate LMI map for % VWC and deadgrass (Figure 4h) shows the expected negative relationship between these two variables in the pink and pale blue areas where High-Low and Low-High areas show significant spatial clusters with high VWC associated with low % deadgrass, or low VWC associated with high % deadgrass. However, the red and dark blue areas show significant spatial clusters with high VWC and high % deadgrass and low VWC and low % deadgrass. In these areas it is clear that it might be possible to reduce the amount of water received. Unfortunately, these features are not consistent across existing irrigation zones. For Figure 4i, the bivariate LMI between VWC and NDVI meter data suggests that more water may be needed in the dark blue Low-low areas, and less in the High-low pink areas.

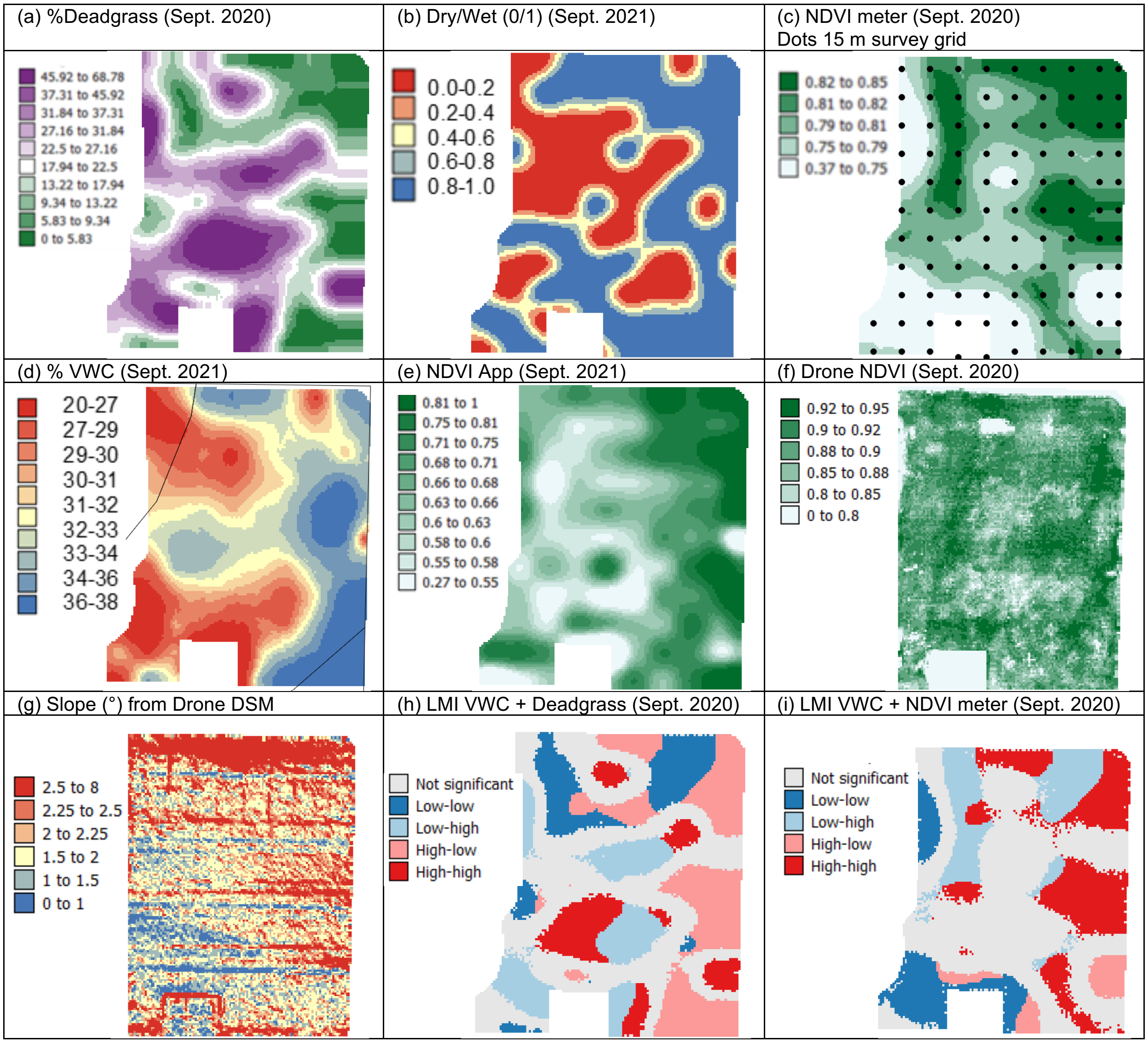


Figure 4. Maps of Harmon field showing (a) Kriged % Deadgrass (Sept. 2020), (b) kriged dry/wet (0/1) (Sept. 2021), (c) kriged NDVI meter data (Sept. 2020), (d) kriged % VWC (Sept. 2021), (e) kriged NDVI App data (Sept. 2021), (f) drone NDVI (Sept. 2020), (g) Slope (°) from drone DSM, (h) Bi-variate LMI for VWC and Deadgrass (Sept. 2020) and (i) Bi-variate LMI for VWC and NDVI meter data (Sept. 2020)

The patterns of variation in the Temple field (Figure 5) do not seem to relate to patterns of variation in elevation (Figure 2c) which is not particularly surprising given the unpredictable patterns of soil texture within this field. Given the elevation patterns of the field, the unexpected dry areas at the base of the slope (western side of the field) could be related to the combination of the soil texture patterns and the management practice of applying 30% less water to the three rows of sprinklers at the base of the slope. Unlike the Harmon field, the temple field is showing some of the greenest areas being associated with some of the driest locations such as in the SW corner and central eastern part of the field (Figure 5b and d). This suggests that there may be significant amounts of over-watering occurring in this field. The black lines on the maps in Figure 5 b and d show the optimum zones developed using the kriged NDVI meter and % VWC data, respectively. The bivariate LMI between VARI data and VWC shows that, the VWC zones essentially identify the significant spatial clusters of Low-high areas (pale blue) where VARI is low, but VWC is high. These areas are probably receiving too much water. The VWC zones also identify the significant spatial clusters of High-low values (pink) where VARI is high, but VWC is low. These areas suggest that the amount of water currently applied is sensible.

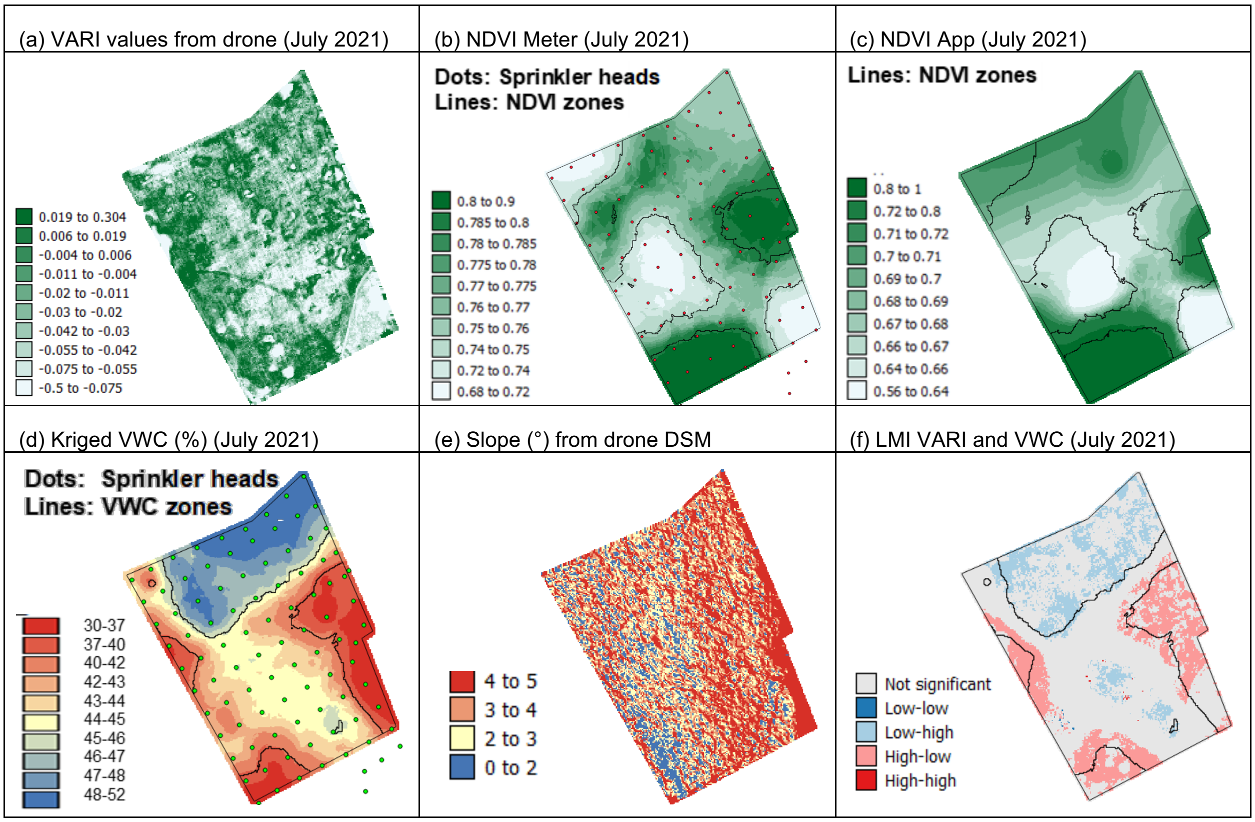


Figure 5. Maps of Temple field showing (a) VARI index values from July 2021 drone image, (b) Kriged NDVI Meter values (July 2021), (c) Kriged NDVI App values (July 2021), (d) Kriged VWC values, (e) Slope (°) from drone DSM and (f) bivariate LMI between VARI and VWC (July 2021). (Black lines show optimal zones developed for that variable)

Figure 6 shows optimal zones for Harmon and Temple fields created using different variables and from different time periods. The zones in the NW and the SE of the Harmon field in Figures 6 a and c are consistent with the different soil types identified by the NRCS web soil survey (see black lines in Figure 4d). Also, in each of these classifications, generally the large central area of the field is one class. Table 2 shows the calculated errors associated with treating the whole field the same, using existing zones and using optimal zones defined in different ways. When the field is treated as a whole or the zones are defined just by soil series, the mean errors are several orders of magnitude greater than when other zones are used. Important, along with the mean errors, is the range of errors and the standard deviation of them. The range and standard deviation are lowest, as might be expected, for S21 VWC zones. Next best performing after this was zones that were based on VWC from all survey dates. However, using Wet-dry zones from the same season or NDVI or all variables from the previous season performed more poorly than the existing zones but better than treating the whole field as if it was one zone. Also, zones based on the wet/dry indicator performed better than the NDVI meter measurements suggesting that residential customers may be able to determine zones by merely touching or looking at the topsoil to see if it looks or feels wet or dry.

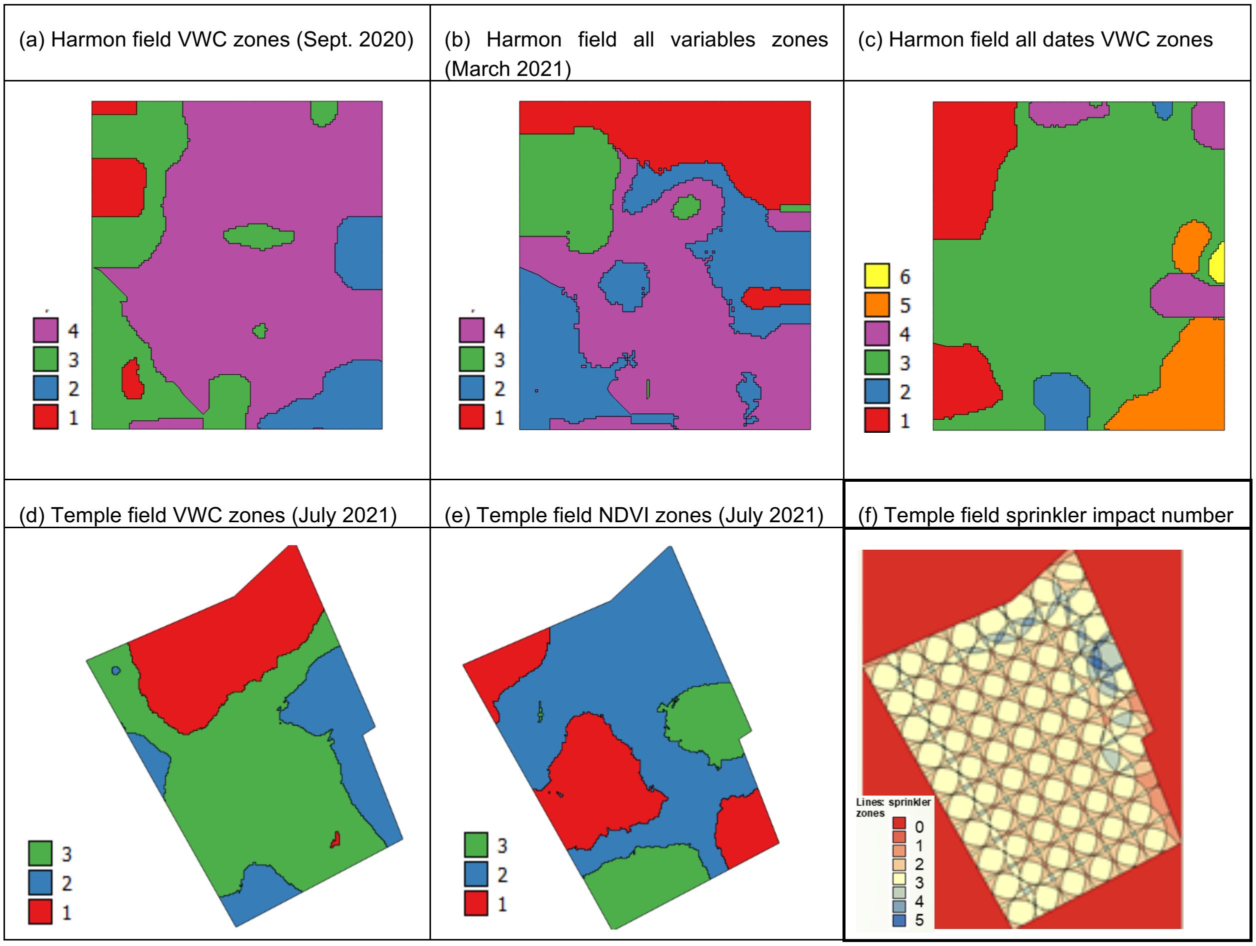


Figure 6. Maps showing the configuration of zones for Harmon and Temple Field based on different variables and data from different dates.

Table 2. Errors between kriged VWC (Harmon, S21, Temple J21) and Average VWC per field or zone based on zones calculated with different variables

Zone Type	Mean	Min.	Max.	St. Dev.
Harmon Field - 1 zone	0.0060123863	-11.54	12.30	4.23
Harmon Existing Zones	-0.0000000002	-16.83	10.68	3.38
Harmon Soil Series zones	3.93	-15.31	19.77	4.95
Harmon S21 VWC zones	-0.0000009402	-5.34	6.00	1.63
Harmon All dates VWC zones	-0.0000006620	-8.16	8.33	2.64
Harmon S21 Wet_Dry zones	0.0000017661	-9.82	10.49	3.80
Harmon S20 All Variables Zones	-0.0000010915	-10.52	13.29	3.98
Harmon S20 NDVI zones	0.0000014605	-11.68	12.33	4.17
Temple Field – 1 zone	$-9.6*10^{-14}$	-8.82	13.07	3.98
Temple Field – Existing zones	$6.21*10^{-21}$	-0.00018	0.000151	0.000031
Temple Field – J21 VWC zones	0.0000004955	-6.85	4.16	1.59
Temple Field –J21 NDVI zones	0.0000014631	-14.26	8.67	3.39

For Harmon field, given that zones based on the VWC data for all dates were the second-best performing zone delineation, VWC for each measurement time was mapped (Figure 7). As mentioned earlier, both an E-W pattern and a N-S pattern is evident for these data with the latter being slightly stronger for the VWC data. The N-S pattern is most pronounced for March 2021 which was outside of the irrigation season and is likely to reflect the natural, long-term soil moisture patterns. The black lines in Figure 7 show the zones based on March 2021 VWC and how they relate to patterns in VWC levels from other surveys. Clearly, from the legends of the maps in Figure 7, the range of VWC in the field changes from time to time but there is a general pattern of the southerly 5 zones having larger % VWC than the northerly zones. Indeed, the black dots show the locations of sensors that have been installed in this field which could help determine the amount of water needed in these two sets of existing zones and could also determine if irrigation rates should be varied within the northerly and southerly zones as there are sensors within two of the northerly and two of the southerly zones.

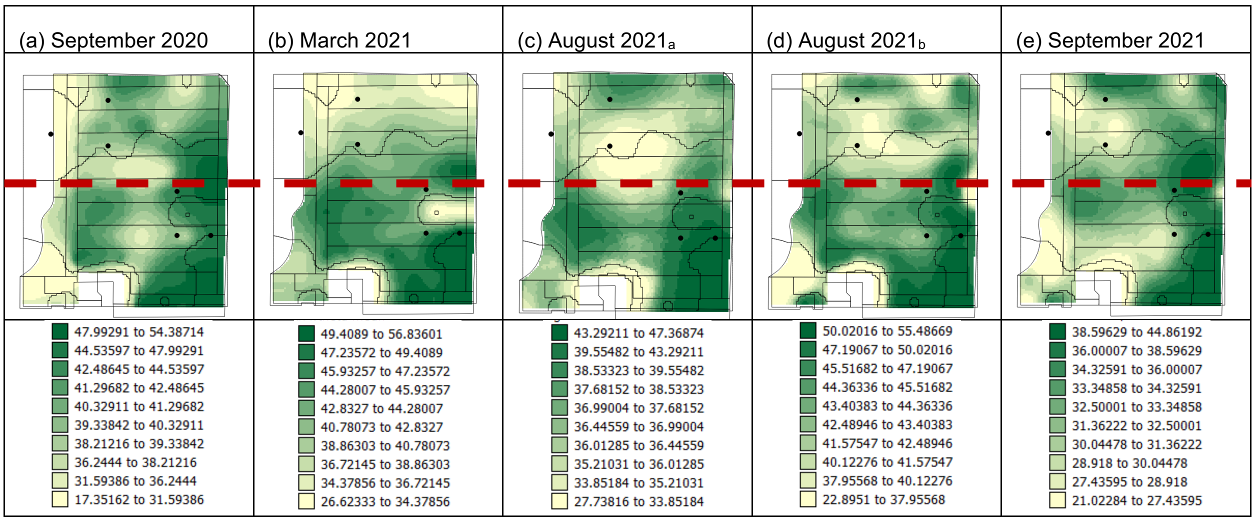


Figure 7. Maps of % VWC for Harmon field for (a) September 2020, (b) March 2021, (c) August 2021$_a$, (d) August 2021$_b$ and (e) September 2021. (Black dots show locations of soil moisture sensors and data loggers

For Temple field, the range of errors and the standard deviations (Table 2) show that if existing zones, these being each individual sprinkler head, are used, errors are orders of magnitude lower than if the field is treated as one zone. However, the full potential of the valve in head sprinkler technology has not been utilized in this field due to the complicated nature of changing the irrigation rate for every individual sprinkler head. The errors also show that, like Harmon field, zones based on VWC values (Figure 6d) are more effective than NDVI zones (Figure 6e). This makes sense as there are several other factors that can affect grass greenness other than VWC such as nutrient levels, soil texture and compaction. The VWC zones being better than NDVI -based zones is also confirmed by the bi-variate LMI analysis of VARI and VWC which showed that the VWC zones identify the wettest and driest zones well and that the LMI analysis can help determine which zones are being over- or under-watered and thus need more or less water. Although the VWC zones have higher errors than using each sprinkler head as its own zone, implementing use of these zones would be far simpler than calculating how much water to apply to each individual sprinkler head for each irrigation event. Also, determining the application procedure for each individual sprinkler head is complicated by the overlap in zone coverage and it is difficult to calculate exactly how much water the area served by each sprinkler head would be getting (Figure 6f).

Conclusions

This analysis suggests that sprinkler zones for irrigation of turfgrass in large general sports fields are best determined through spatial surveys of soil moisture rather than surveys of several different variables or by NDVI and other measures of grass health. This analysis also suggests that patterns in VWC change temporally and that it would be best to redefine spatial zones before each irrigation event. However, this would require significant investment in automated sensing and mapping equipment that could communicate with a smart sprinkler system which could be restrictively expensive given that no crop is produced for sale by turfgrass that can offset the price of survey and sensing equipment. Given that there are similarities in patterns of VWC over time that relate to patterns of slope and soil texture and that using VWC data from all sampling times to define zones was the second-best performing type of zone, an average of VWC values from several surveys taken at different times within the season or zones based on soil moisture levels before the irrigation season starts would be sensible. Mapping the wet/dry indicator shows promise as an inexpensive survey method as it is more helpful than NDVI data or information on dead or discolored grass. The ability of EM38 surveys to identify zones within turfgrass fields and determine their consistency should be evaluated as these are relatively swift non-invasive surveys which have proved useful in determining zones for various aspects of Precision Agriculture. Consulting firms could potentially determine zones using such equipment just once per location. Another possibility to investigate is drought indices from thermal IR drone imagery to determine if the same locations are consistently experiencing water deficit throughout the irrigation season. The final question that needs addressing is that once irrigation rates are modified to fit the optimal zones that are defined, will the management effect of varying rates between zones significantly affect the spatial patterns in soil moisture? If so, this would mean that zones need to be constantly re-defined making it imperative to find inexpensive, automated ways of sensing soil moisture patterns.

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