Spatio-temporal Analysis of Soil Moisture and Turfgrass Health to Determine Temporally Stable Variable Rate Irrigation Zones

Ruth Kerry[1], Kirsten Sanders[1] Abigail Henrie[1], Ashley Swenson[1], Ben Ingram[2], Neil Hansen[3], Bryan Hopkins[3]

[1]Geography Department, Brigham Young University, UT, USA,

[2]School of Water, Energy and Environment, Cranfield University, Bedfordshire, UK,

[3]Plant and Wildlife Science Department, Brigham Young University, UT, USA

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Abstract.

The western USA has been in severe drought for the last 20 years. Yet in urban areas in Utah irrigated turfgrass lawns are the norm. The EPA has estimated that about 50% of residential turfgrass irrigation is wasted through spatial and temporal mis-applications. Valve in head sprinkler heads allow different amounts of water to be applied by each sprinkler head so that each head is essentially an individual sprinkler zone. However, for this to work effectively, custom soil moisture zones need to be identified for each site. For precision irrigation of traditional crops it has been suggested that irrigation zones should be frequently reassessed. However, with turfgrass there is no crop to offset the cost of frequent sensing and re-mapping so static irrigation zones are desirable. This study involves spatio-temporal analysis of soil moisture and remotely sensed data to try and determine areas of two large sports fields that behave consistently in space and time and those that are changeable temporally. Spatial fields surveys (2-5 a year) of the two large sports fields from a 4-year period are investigated along with National Agricultural Imagery Program (NAIP) aerial imagery from 2006-2021. Principal components analysis is used to determine similarities and differences in the behavior of the soil moisture and NAIP imagery. Determining the areas that behave consistently in time means that soil moisture can be managed using static irrigation zones based on those areas until economic ways of producing new zone maps before each irrigation event are developed.

Keywords. *Turfgrass, Variable Rate Irrigation, Soil Volumetric Water Content, Aerial Imagery, Principal Components Analysis*

Introduction

The western USA has been experiencing severe drought conditions for at least the last 20 years (Williams et al. 2020). The population in many areas of the west, like Utah, has also increased greatly in this time putting greater strain on the limited freshwater supply (Derouin, 2017). While agriculture is generally the sector consuming the largest proportion of freshwater, conversion of agricultural land to urban areas with lawns, parks and playing fields may result in some reduction of water use, but the EPA have estimated that as much as 50% of residential turfgrass irrigation is wasted through spatial and temporal mis-applications (EPA, 2017). Temporal misapplications can be resolved by using smart sprinkler systems that take local weather conditions into consideration when determining irrigation timing (Serena et al., 2020). Valve in head sprinkler heads allow different amounts of water to be applied by each sprinkler head so that each head is essentially an individual sprinkler zone. Ideally, based on what has been learned from precision irrigation of arable crops, the soil moisture should be mapped/inferred between each irrigation event to create new temporally varying zone application maps (O'Shaughnessy et al., 2015) to work with the valve in head technology. With turfgrass no crop is sold to offset the cost of the spatial sensing or survey needed to make temporally varying zone maps. Unfortunately, the technology to economically create new irrigation zone application maps for each irrigation event for use with valve in head sprinkler heads for turfgrass is currently lacking. Kerry et al. (2023) investigated the potential for electrical conductivity (ECa) and drone data to characterize the spatial variability of soil moisture in turfgrass. They noted that due to extra permissions that are needed and no fly zones in urban areas, drone data was less useful for the potential mapping of temporally changing variable rate irrigation zones for urban turfgrass. They also found that due to many conductive features in the urban environment, mapping using ECa data is more labor intensive in urban rather than agricultural areas. They concluded that ECa data modelled the variation in soil moisture better than drone data, but that even if the EM38 were pulled behind a lawn mower whilst mowing, any semi-automated mapping resulting from the data would only be economical for high value sport's fields like golf courses or football stadiums where there is income to pay for the sensor, repeated sensing and automated mapping.

Based on the conclusions of the work of Kerry et al. (2023), this study takes a step back to look at static variable rate irrigation zones. If zones are to be static, then there is a need to identify which patterns in soil moisture are static in time and which vary temporally. The study involves spatio-temporal analysis of turfgrass health, soil moisture and remotely sensed data to try and determine areas of two large sports fields that behave consistently in space and time and those areas that are changeable temporally. Spatial fields surveys (2-5 a year) of the two large sports fields from a 4-year period are investigated along with National Agricultural Imagery Program (NAIP) aerial imagery from 2006-2021. Principal components analysis (PCA) is used to determine similarities and differences in the behavior of the soil moisture and turfgrass in space and time. Determining the areas that behave consistently in time means that one always knows something about the likely patterns of soil moisture and can manage it accordingly until economic ways of producing new zone maps before each irrigation are developed.

Methods

Field Sites

The field sites for this study were two turfgrass fields on Brigham Young University campus in Provo, Utah, USA. The fields grow Kentucky blue grass and have the following dimensions and locations: Harmon field (150 m x 115 m) (40.256°N, 111.644°W), MTC field (200 m x 150 m) (40.262°N, 111.644°W). Slopes in the Harmon field range from 1-6% and in the MTC field they are 3-6%. Both fields have soils that have been partially engineered, but https://websoilsurvey.sc.egov.usda.gov/App/WebSoilSurvey.aspx, shows that the native soils in the Harmon field were predominantly of the Taylorsville silty clay loam and for the MTC field they were Pleasant Grove gravelly loam soils before engineering.

Harmon field had traditional sprinkler zones mostly aligned with changes in elevation (Figure 1a) and MTC field had valve in head sprinkler heads. Each sprinkler head forms its own zone covering a radius of 27 m (see red lines in Figure 1b). Sprinkler heads are spaced at 20 m so there is overlap in the area covered by different heads (see intersecting black circles in Figure 1b).

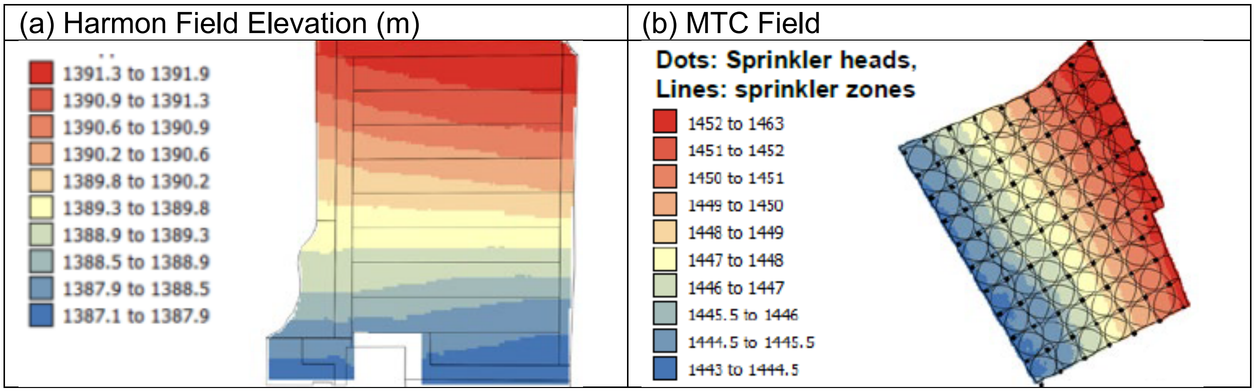

Figure 1. Maps showing the Variation in Elevation, Sprinkler Heads (black dots), Sprinkler Zones (black lines) within (a) Harmon Field and (b) MTC Field

The Harmon field was surveyed on 13 dates: Sept. 2020, March 2021, Aug. 2021a, Aug. 2021b, Sept. 2021a, Sept. 2021b, April 2022, May 2022, Oct. 2022, April 2023, May 2023, July 2023 and Sept. 2023 and the MTC field was samples on 9 dates: July 2021, Sept. 2021, April 2022, May 2022, Oct. 2022, May 2023, June 2023, July 2023 and Sept. 2023. The Harmon and MTC fields were sampled on 15 m and 20 m grids, respectively (Figure 2). At each grid node in the field soil volumetric water content (VWC) was measured using a Delta T theta probe calibrated for loamy soils. Other observations made at each grid node were: normalized difference vegetation index (NDVI) measured using a Trimble Greenseeker, Wet-Dry indicator (WD) which was an indication of whether the grass felt dry (0), damp (0.5) or wet (1) to the touch and % Deadgrass (%DG) which was an estimate of the percentage of grass that was dead of discolored within a 0.5 m x 0.5 m quadrat.

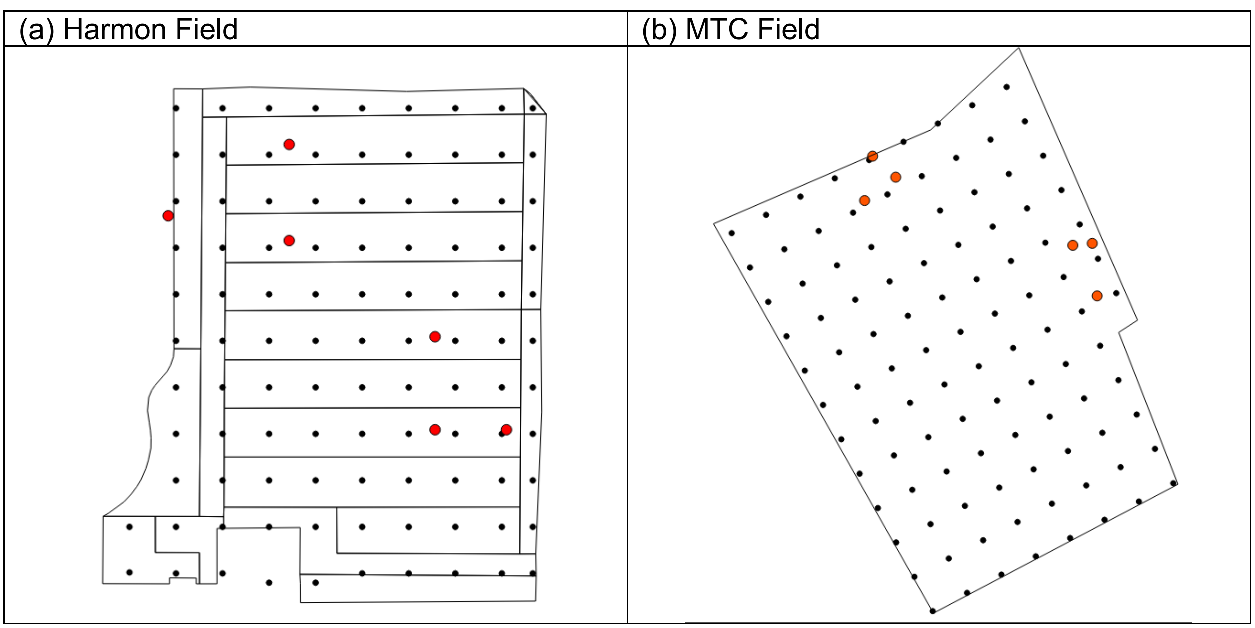

Figure 2. Maps showing Sampling Points (black dots) and Sensor Locations (red dots) in (a) Harmon Field and (b) MTC Field

Aerial Imagery

NAIP Imagery (National Agricultural Imagery Program) are the result of surveys that are performed every 3 years. For Provo, Utah, where the field sites are located, the surveys are performed in August of each survey year. The NAIP imagery data are available free of charge and were downloaded from https://earthexplorer.usgs.gov/. The NAIP imagery pixel size (1 m) is much more suited to turfgrass study than other freely available imagery such as Landsat and Sentinel data where the pixels sizes (30 m and 10 m, respectively) are too large given the size of the fields. NAIP imagery was available for both fields from flights made in August 2006, 2009, 2011, 2014, 2016, 2018 and 2021. The wavelengths measured were only RGB in 2006 and 2009, but NIR was also measured from 2011 onwards so the NDVI could be calculated. Shape files of the field boundaries were used to extract the imagery for only the extent of the fields of interest. The imagery data for each field were converted to digital numbers for analysis. As the northern part of the Harmon field was dug up in 2014, the 2014 data were excluded from the Harmon field NAIP PCA analysis.

Statistical Analysis

All soil survey data from both field sites were kriged to the same 1 m grid as the NAIP imagery using SpaceStat (Jacquez, 2014). A time series principal components analysis (PCA) was computed for the following datasets using SPSS (IBM, 2021):

1. RGB, NIR and NDVI from NAIP Surveys for each tri-yearly survey
2. VWC from all field surveys
3. VWC and NDVI from all field surveys
4. Wet-Dry indicator and % Deadgrass from all field surveys

Principal component plots showing the loadings of each variable were investigated and the values of PCs 1 and 2 were mapped for each PCA. Pearson correlations of PC1s and PC2s from different PCA surveys with the NAIP PCs 1 and 2 were calculated.

Results and Discussion

Harmon Field

Figure 3 shows the maps of VWC from each of the 13 surveys for the Harmon Field and Figure 4 shows the images of NAIP imagery from each of the years for the Harmon Field. Correlation analysis showed that VWC from 9 of the surveys was correlated with VWC from other surveys with r = 0.54 to 0.77, however for the other four surveys correlations with the majority of the surveys was low r = -0.08 to 0.387. These correlations can be seen in patterns shown in the VWC maps from each survey (Figure 3). Most have distinct similarities and key features in common between surveys such as areas with low VWCs shown in blue that have been circled in black. For the NAIP imagery data, the different wavebands were moderately correlated (r = 0.28 to 0.52) with each other between some years such as 2006, 2009, 2011 and 2016, but correlations were weak for 2014, 2018 and 2021 (r = 0.02 to 0.20). Nevertheless, as with the VWC survey data, there are key features evident in the patterns of variation where the grass is less green that are consistent across some years which have been circled in red in Figure 4.

Table 1 shows a summary of the PCA results using different time-series of data for the Harmon field. For each PCA apart from the VWC PCA, 6 PCs explain at least as much variation as one of the original variables, or one of the original surveys. For the VWC PCA, only three PCs accounted for as much variation as one of the original variables. For the NAIP imagery and the VWC, the first two PCs accounted for >60% of the variation in the dataset whereas for the VWC & NDVI and WD & DG PCAs the first two PCs only accounted for >40% of the variation in the dataset. This shows that more consistency can be summarized in the first two PCs for the NAIP imagery and the VWC data rather than the other two PCAs. The variables with the greatest and smallest loadings in terms of PC1 were green and NDVI for 2011 for the NAIP imagery PCA and were July and September 2023 for the VWC PCA. Figure 3 shows that these two months have the most different VWC patterns of all the Harmon VWC surveys. For the variables that are unrelated to PC1 in each PCA, the NIR for 2018 and 2021 stand out for the NAIP imagery and for the VWC & NDVI PCA, the NDVI measurements from March 2021 and April 2023 stand out. This is likely because the turfgrass may not have fully greened up following the winter dormancy period.

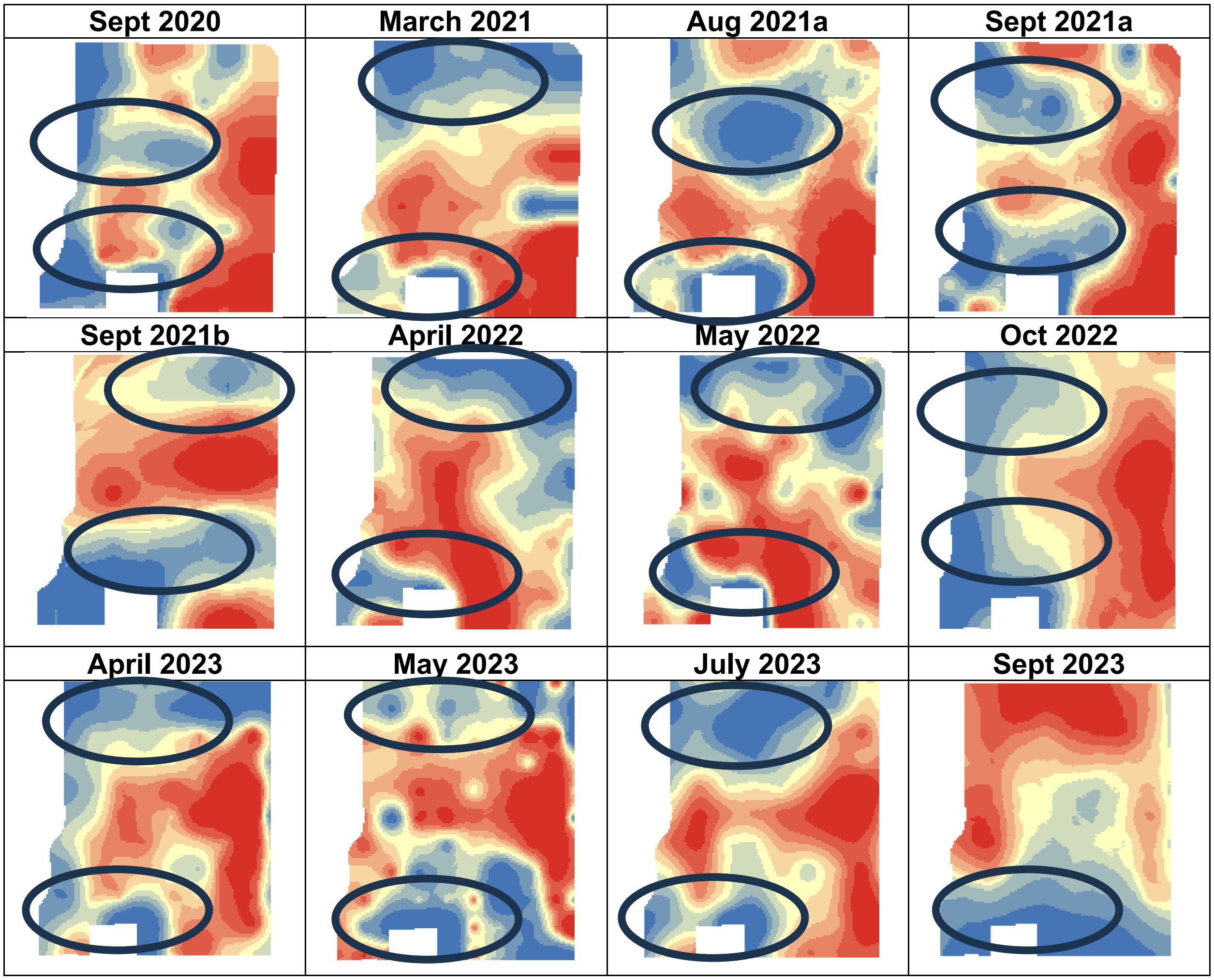

Figure 3. Maps of Kriged VWC for Harmon field for Different Survey Dates (Red areas show wetness and blue areas show dryness)

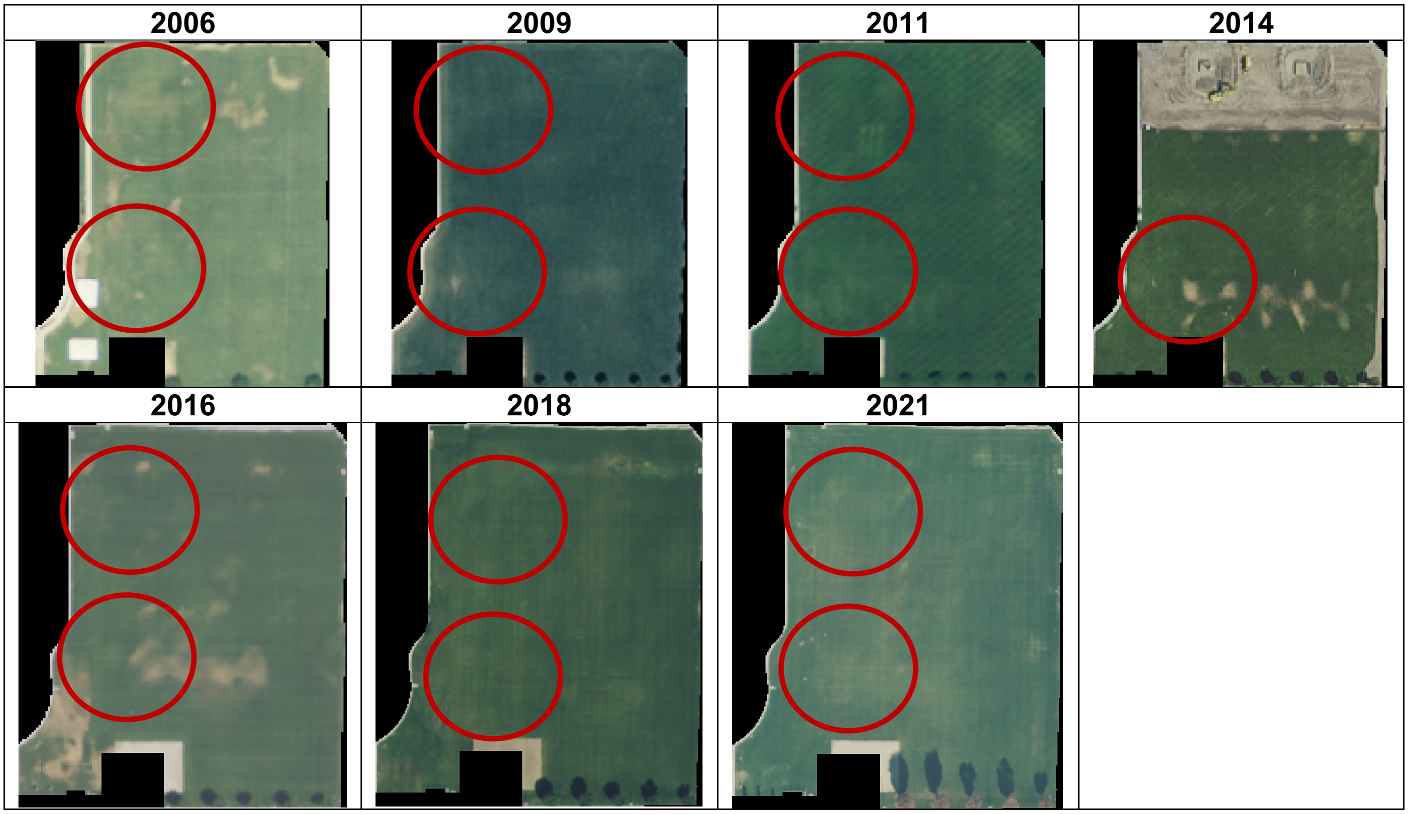

Figure 4. NAIP images for Harmon Field from Different Years

Table 1. Summary of Time Series Principal Components Analyses for Harmon Field

PCA	Number of PCs meeting Kaiser's Criterion	% Variance Covered by PCs 1 and 2	Variables with highest and lowest PC 1 loadings	Variables unrelated to PC1
NAIP imagery	6	60.07	Green 2011 NDVI 2011	NIR 2018 NIR 2021
VWC all surveys	3	63.56	July 2023 VWC Sept 2023 VWC	None
VWC and NDVI all surveys	6	49.94	Sept 2021 VWC Sept 2023 VWC	Mar. 2021 NDVI Apr. 2023 NDVI
WD and % DG all surveys	6	40.62	July 2023 DG Oct. 2022 WD	Mar. 2021 WD Sep. 2020 DG

NAIP = National Agricultural Imagery Program, VWC=Volumetric Water Content,
NDVI = Normalized Difference Vegetation Index, WD = Wet/dry indicator, DG = % Deadgrass

Figure 5 shows maps of PC1 and PC2 for each PCA. Some of the features that were circled in black and red in Figures 3 and 4 are evident in some of the PC plots and have been circled in black. Table 2 shows the correlations with NAIP PCs 1 and 2 for PCs 1 and 2 of PCAs for different variables. PCs1 from the VWC and VWC & NDVI PCAs have moderate negative correlations with PC1 from the NAIP imagery. In contrast, the DG & WD PC1 had a moderate positive correlation with NAIP PC1. The correlations between NAIP PCs 1 and 2 are far lower for other PCs. These results suggest that NAIP PC1 is identifying the main features of variation in grass health and these correlate moderately with the main features in VWC, VWC & NDVI and DG & WD surveys. However, given that PCs1 and 2 account for >60% of the variation for the NAIP and VWC PCAs, the correlations suggest that time series NAIP imagery and time series VWC surveys are equally successful at identifying the key features of variation that are stable over time and that the NAIP imagery could be used to identify static, precise irrigation zones for the Harmon field at no cost for collecting the data.

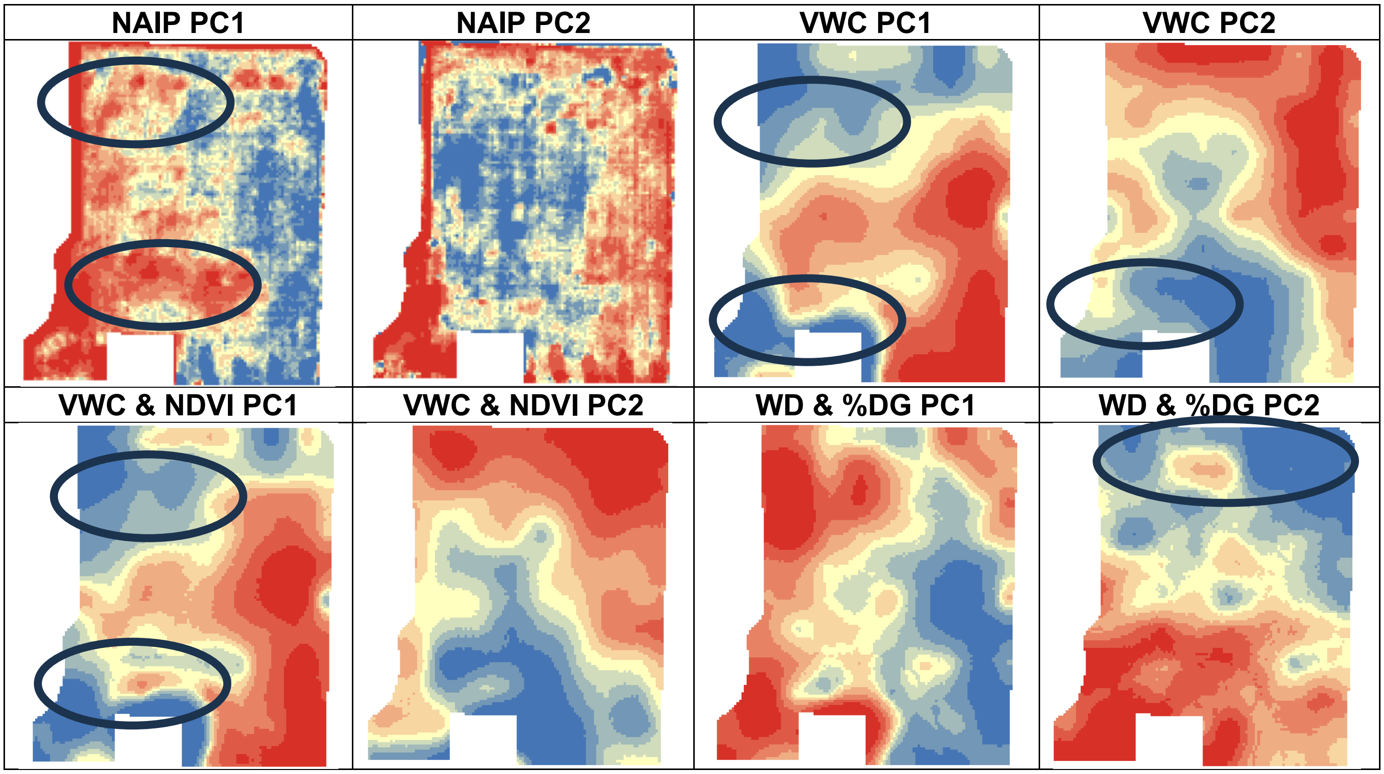

Figure 5. Plots of PCs 1 and 2 for different Principal Component Analyses in Harmon Field (Red: positive values of PC1 and 2 and Blue: negative values of PC1 and 2)

Table 2. Correlations with NAIP PCs 1 and 2 for Harmon Field

Variable 1	Variable 2	*r*	Variable 1	Variable 2	*r*	Variable 1	Variable 2	*r*
NAIP PC1	VWC PC1	-0.40	NAIP PC1	VWC & NDVI PC1	-0.41	NAIP PC1	DG & WD PC1	0.41
NAIP PC1	VWC PC2	-0.13	NAIP PC1	VWC & NDVI PC2	-0.01	NAIP PC1	DG & WD PC2	0.18
NAIP PC2	VWC PC1	-0.08	NAIP PC2	VWC & NDVI PC1	-0.04	NAIP PC2	DG & WD PC1	0.11
NAIP PC2	VWC PC2	0.06	NAIP PC2	VWC & NDVI PC2	0.14	NAIP PC2	DG & WD PC2	0.19

NAIP = National Agricultural Imagery Program, VWC=Volumetric Water Content,
NDVI = Normalized Difference Vegetation Index, WD = Wet/dry indicator, DG = % Deadgrass
PC = Principal Component

MTC Field

Figure 6 shows the maps of VWC from each of the 9 surveys for the MTC Field and Figure 7 shows the images of NAIP imagery from each of the years for the MTC Field. Correlation analysis showed that VWC from two thirds of the surveys was moderately to strongly correlated with VWC from other surveys with r = 0.30 to 0.81, however for the other surveys correlations between VWCs values was low r = -0.08 to 0.299. These correlations can be seen in patterns shown in the VWC maps from each survey (Figure 6). Most have distinct similarities and key features in common between surveys such as areas with high VWCs shown in red that have been circled in black at the center and northern end of the field (Figure 6). For the NAIP imagery data, the different wavebands were moderately to strongly correlated (r = 0.30 to 0.71) with each other between some years such as 2009, 2011, 2016, 2018 and 2021, but correlations were weaker for 2006 and 2014 (r = 0.02 to 0.40). Nevertheless, as with the VWC survey data, there are key features evident in the patterns of variation where the grass is less green in the center of the field (see red circles in Figure 7) and darker green in the north of the field (see blue arrows in Figure 7) that are consistent across some years.

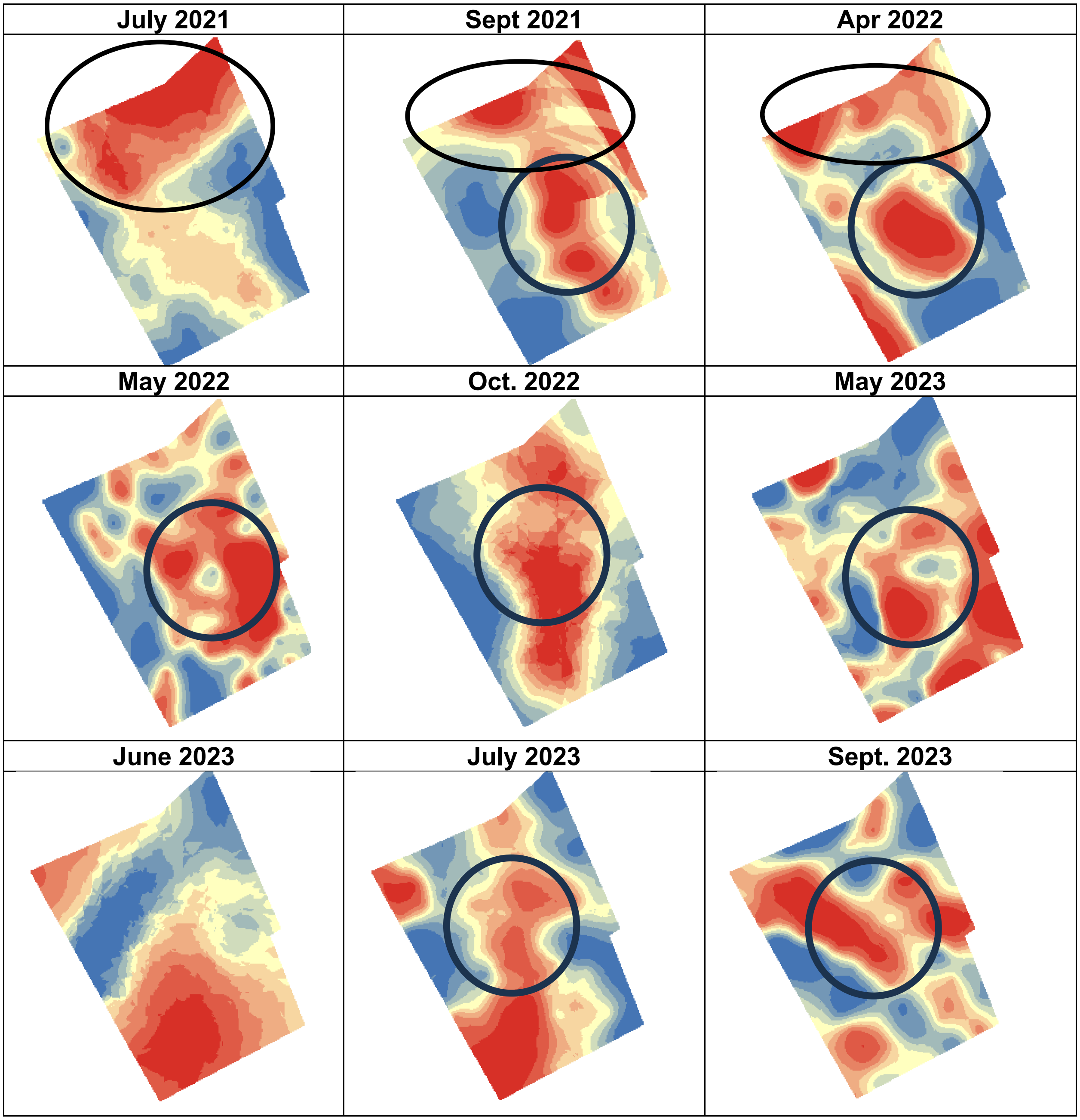

Figure 6. Maps of Kriged VWC for MTC field for Different Survey Dates (Red areas show wetness and blue areas show dryness)

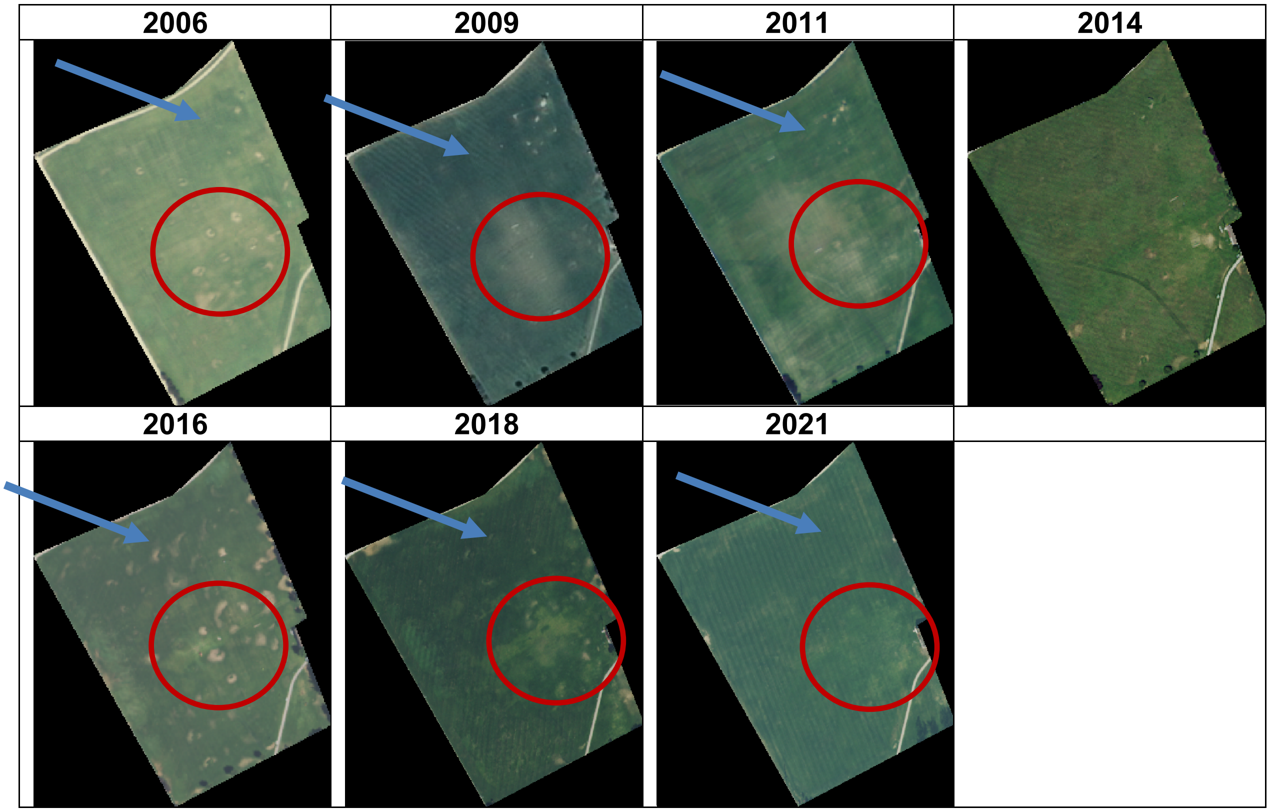

Figure 7. NAIP images for MTC Field from Different Years

Table 3 shows a summary of the PCA results using different time-series of data for the MTC field. For each PCA, 4-9 PCs explain at least as much variation as one of the original variables, or one of the original surveys. For the NAIP imagery, VWC and WD & DG PCAs, the first two PCs accounted for >50% of the variation in the dataset whereas for the VWC & NDVI PCA the first two PCs only accounted for 42.93 % of the variation in the dataset. This shows that more consistency can be summarized in the first two PCs for the NAIP imagery, VWC and the WD & DG data rather than the VWC & NDVI PCA. The variables with the greatest and smallest loadings in terms of PC1 were blue and NDVI for 2018 for the NAIP imagery PCA and were October 2022 and May 2023 for the VWC PCA. This suggests that these two months have the most different VWC patterns of all the MTC VWC surveys (see Figure 6). For the variables that are unrelated to PC1 in each PCA, the NIR and blue for 2014 stand out for the NAIP imagery and for the VWC, VWC & NDVI and the WD & DG PCAs, May and June 2023 VWC and September and May 2023 DG stand out. This is likely because the maps for VWC of May and June 2023 are markedly different from the maps of other surveys with high values of VWC at the north end of the field being absent.

Figure 8 shows plots of PC1 and PC2 for each PCA. Some of the features that were circled in black and red and pointed to with blue arrows in Figures 6 and 7 are evident in some of the PC plots and have been circled in black. Table 4 shows the correlations with NAIP PCs 1 and 2 for PCs 1 and 2 of PCAs for different variables. The correlations between NAIP PCs 1 and 2 are low with all other PCs (Table 4). This likely because the areas that are identified as having high VWCs in Figure 6 in the north and center of the field have darker and lighter colored green grass, respectively. This means that there are areas of the field where there is a positive correlation between VWC and NAIP imagery values and other areas of the field where there is a negative correlation which means that overall the correlations are weak. The center of the field corresponds to an area that is played on the most and is compacted with higher VWC near the surface.

Table 3. Summary of Time Series Principal Components Analyses for MTC Field

PCA	Number of PCs meeting Kaiser's Criterion	% Variance Covered by PCs 1 and 2	Variables with highest and lowest PC 1 loadings	Variables unrelated to PC1
NAIP imagery	9	50.96	Blue 2018 NDVI 2018	NIR 2014 Blue 2014
VWC all surveys	5	50.81	Oct. 2022 VWC May 2023 VWC	May 2023 VWC
VWC and NDVI all surveys	7	42.93	Oct. 2022 VWC Sept. 2021 NDVI	June 2023 VWC
WD and % DG all surveys	4	52.55	Sept 2023 WD July 2023 DG	Sept 2023 DG May 2023 DG

NAIP = National Agricultural Imagery Program, VWC=Volumetric Water Content,
NDVI = Normalized Difference Vegetation Index, WD = Wet/dry indicator, DG = % Deadgrass

The area at the north end of the field, however, is a relatively flat area towards the top of a lesser, north-south running slope and therefore is wetter. Clearly, different processes are at work in both of these locations to make the soil wetter, hence the reverse correlations between VWC data and NAIP imagery in these two areas are evident. Despite the overall low correlations, Figure 8 shows that several key features (circled in black) that were prevalent in the soil and vegetation surveys have been identified in the NAIP imagery so it is still likely that it could be used to identify static irrigation zones for variable rate irrigation as areas which behave relatively consistently in time have been identified by the NAIP and other PCAs.

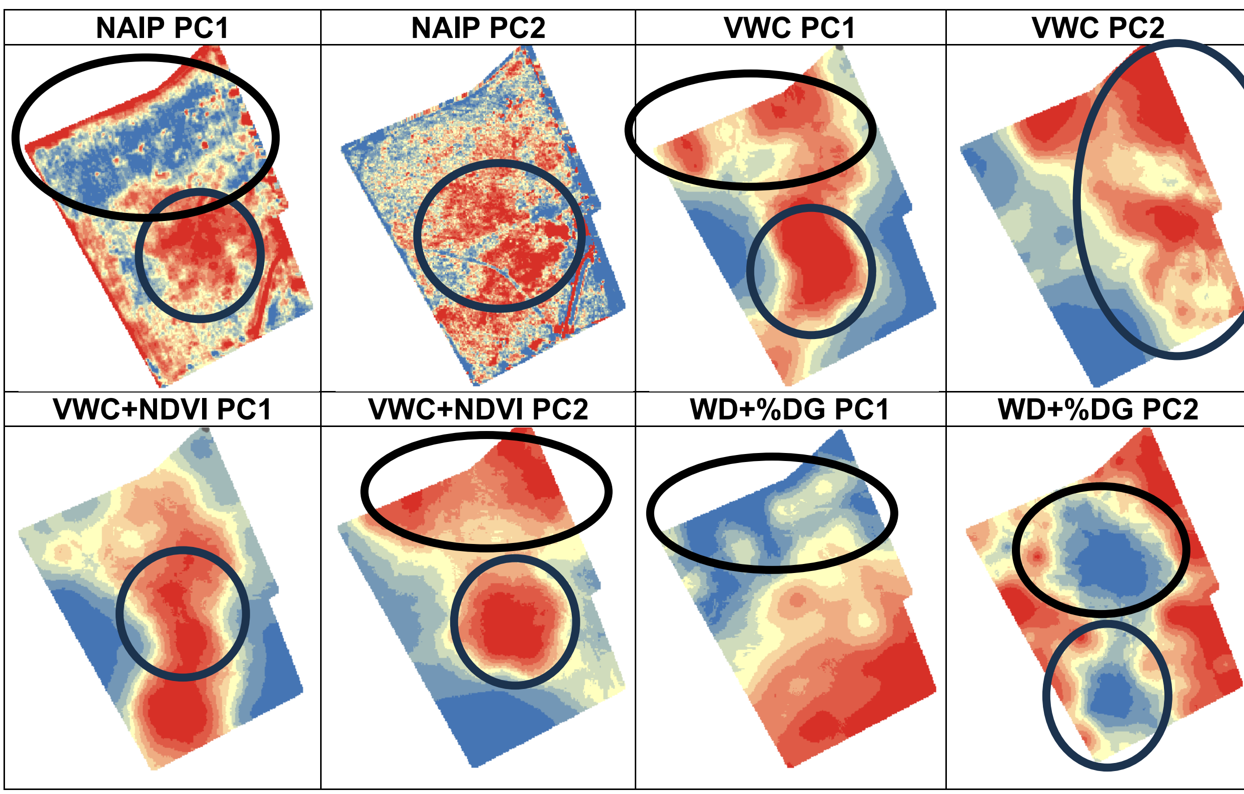

Figure 8. Plots of PCs 1 and 2 for different Principal Component Analyses in MTC Field (Red: positive values of PC1 and 2 and Blue: negative values of PC1 and 2)

Table 4. Correlations with NAIP PCs 1 and 2 for MTC Field

Variable 1	Variable 2	*r*	Variable 1	Variable 2	*r*	Variable 1	Variable 2	*r*
NAIP PC1	VWC PC1	-0.04	NAIP PC1	VWC & NDVI PC1	-0.11	NAIP PC1	DG & WD PC1	0.23
NAIP PC1	VWC PC2	0.15	NAIP PC1	VWC & NDVI PC2	0.03	NAIP PC1	DG & WD PC2	0.18
NAIP PC2	VWC PC1	0.19	NAIP PC2	VWC & NDVI PC1	0.20	NAIP PC2	DG & WD PC1	0.11
NAIP PC2	VWC PC2	-0.04	NAIP PC2	VWC & NDVI PC2	0.06	NAIP PC2	DG & WD PC2	-0.14

NAIP = National Agricultural Imagery Program, VWC=Volumetric Water Content,
NDVI = Normalized Difference Vegetation Index, WD = Wet/dry indicator, DG = % Deadgrass
PC = Principal Component

Conclusions

PCA analysis for times series VWC surveys, VWC & NDVI surveys and WD & DG surveys showed similar results to PCA analysis of times series NAIP imagery wavebands. The field surveys, particularly the VWC survey and VWC & NDVI survey are labor intensive, but if a PCA of a times series of the freely available NAIP imagery can identify similar key features in PCs 1 and 2 or correlates at least moderately with the VWC PCA, then this suggests that a PCA of time series NAIP imagery is a valid approach to identifying areas that behave consistently in time and thus can identify static variable rate irrigation zones. The NAIP imagery proved useful at both field sites for identifying key patterns in soil moisture variation that are consistent in time, however, the two main, consistently wet areas, in the MTC field were wet for different reasons and thus the turfgrass response in the NAIP imagery was the opposite for these two wet patches. Future work will involve confirming this analysis using a Random Forest approach to both classification and also where PC 1 for the VWC times series of surveys is used as the dependent variable and the NAIP imagery reflectances for each waveband and year are used as the independent variables. This will confirm the predictability of the VWC patterns that are consistent in time using zones based on the NAIP imagery.

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