# GIS in Water Resources CEE 6440

"Optimal representation of plants & soils characteristics using high resolution imagery"



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# Outline

1. Introduction: Precision Agriculture	
2. Project site	4
3. Data Collection	5
3.1 Real- time Data	5
3.2. Sampling Data	6
3.3. Ariel Imagery	7
4. Objectives & Motivation	9
4.1 Objective one: Time Series Interpolation	9
4.2 Objective two: Generating Maps	13
5. Conclusion	17
6. References	
Appendix	19

# List of Figures

Figure 1 Millard County in Utah
Figure 2 Landsat image of Scipio showing the center pivots in Red
Figure 3 To the left: placing the sensors at one and two foot, to the right the weather6 station
Figure 4 Taking the Chlorophyll reading with SPAD 520 during the UAV flight6
Figure 5 A high resolution image of the site in Red, Green and Blue bands7
Figure 6 to the left: The Raven launching, to the right: the cameras are removed from the UAV and images are retrieved
Figure 8 Location of sensors on the RGB-NIR map10
Figure 9 Iteration over time steps to reach IDW interpolation11
<ul> <li>Figure 10 IDW interpolation of (a) Temperature (b) Soil Moisture at 2 foot, (c) Soil Moisture at 1 foot, (d) Soil Electrical Conductivity</li></ul>
Figure 12 Chlorophyll Map of the field16

# List of Tables

Table 1: Data gathered from the sensors	9
Table 2: Time enabled table	10
Table 3: Vegetative Indices	13
Table 4: A sample of data from Lab measurements and corresponding pixel v      maps	value in VI ` 15

#### **<u>1. Introduction: Precision Agriculture:</u>**

Precision Agriculture, a new approach in modern agricultural practices, and perhaps one of the few terms of many definitions. Defining Precision Agriculture varies depending on the objectives, technology and complexity of the operation. New researches addressing this issue constantly broaden our definition of Precision Agriculture by providing management opportunities we as Agricultural Engineers never thought possible. Below is a definition that relates the most to our field of research:

"Precision Agriculture: is adjusting production inputs and practices based on in-field variability through the use of site-specific information, high resolution imagery and precision technologies".

Precision Agriculture (PA) is an integrated crop management system that allows producers to monitor their crops on very fine scales, pinpointing locations of special needs with accuracy to within a few centimeters. This new technology affects the entire production function and largely contributes to agricultural profitability and environmental quality enhancement. Precision Agriculture optimizes site-specific management in mechanized agriculture and is proving to be the next *decision-making-tool* by integrating data, models, GIS maps and others to support better-informed management decisions.

In this project GIS, ERDAS and EXCEL tools will be used to process and analyze high resolution imagery for precision agriculture purposes.

#### 2. Project site:

The project site is located in Scipio, a town in Millard County in Utah (Figure 1). Scipio belongs to the HUC 16030005 known as "Lower Sevier". The Center pivot where the experiment was conducted, highlighted in red in (figure 2), is located at Latitude/Longitude 39.2842°N, 112.1105°W in the UTM zone 12 (404225, 4348903). The center pivot is planted with Alfalfa and Oat crops.



Figure 1 Millard County in Utah



Figure 2 Landsat image of Scipio showing the center pivots in Red

#### 3. Data Collection

The Data collection process was divided into three parts:

3.1 Real- time Data:

Real-time data of soil moisture, salinity and temperature at one and two foot depth from 14 different locations in the field were collected. These data were retrieved from Decagon sensors buried in the soil and connected to a data logger that records these values on hourly bases (figure 3). An Agricultural weather station was also placed in 7 different location in the field it recorded weather related variables (Temperature, wind speed, ....)



Figure 3 To the left: placing the sensors at one and two foot, to the right the weather station

## 3.2 Sampling Data:

Soil samples taken at 3 different depths (0-5,5-10,20-30 cm) were tested in the lab for soil moisture, plant available nitrate-N and ammonium-N using (Method 4500-NO2-B, APHA, 1998) and (Method 4500-NH3 D, APHA, 1998). Plant samples from the two crops were also collected and tested for Total Kjeldahl Nitrogen (TKN) using the phenate method (Method 4500-NH3 D, APHA, 1998) via a Seal AQ2 Discrete Analyzer. Minolta chlorophyll meter (model SPAD 502) was used to assess the Chlorophyll Content Index (CCI) in both crops (figure 4).



Figure 4 Taking the Chlorophyll reading with SPAD 520 during the UAV flight

## 3.3 Ariel Imagery

Raven, an AggieAir UAV, is a fully autonomous, multispectral remote sensing platform with an on-board GPS receiver, and inertial measurement unit (IMU) to navigate according to its preprogrammed flight plan. It carries an RGB, NIR and thermal SX110 camera lenses. During the flight, the three onboard digital cameras take pictures every four seconds. Every time a picture is taken, the position and orientation of the UAV is also recorded for post-processing. The obtained image is composed of Red, Green, Blue, NIR and thermal bands (Figure 5).

Raven flew at an altitude of 450 m above the experiment site making four flight lines for survey starting at NE corner to the NW corner (Figure 6).



Figure 5 A high resolution image of the site in Red, Green and Blue bands.



Figure 6 to the left: The Raven launching, to the right: the cameras are removed from the UAV and images are retrieved.

Global Positioning System (GPS) reading using Trimble R8 GNSS and R6/5800 GPS receiver was recorded for the locations of: soil sampling, sensors, and weather stations (figure 7).



Figure 7. Measuring the GPS of sensor five

#### 4. Objectives & Motivation

The motivation behind our study is to investigate and develop tools that contributes to precision agriculture techniques. The direct objectives related to this report are the following:

1. Visualize the obtained time-series data retrieved from the site and use the inverse distance weight interpolation tool to interpolate values for the entire center pivot over a month period.

2. Use the high resolution image to generate chlorophyll and soil Nitrogen maps to be used in decision making when practicing Precision Agriculture.

#### 4.1. Objective one: Time Series Interpolation

Data obtained from the sensors were exported to EXCEL sheets (Table 1), fields representing the station/sensors numbering, Date and time of measurement and the corresponding values of the 3 different parameters.

station	Data & time	Soil moisture @ 2 foot	Temperature	Electrical
				conductivity
3	9/1/2012 0:00	0.251522	19.8	0.337
3	9/1/2012 1:00	0.250014	19.8	0.336
3	9/1/2012 2:00	0.248852	19.7	0.328
3	9/1/2012 3:00	0.247254	19.7	0.326
3	9/1/2012 4:00	0.2464	19.6	0.32
3	9/1/2012 5:00	0.245982	19.5	0.316
3	9/1/2012 6:00	0.244856	19.4	0.314
3	9/1/2012 7:00	0.24482	19.3	0.315
3	9/1/2012 8:00	0.24393	19.2	0.315
3	9/1/2012 9:00	0.243421	19.2	0.312

Table 1: Data gathered from the sensors.

Following that a Geodatabase is created with a feature class, the high resolution (13 cm\*13cm) UAV image composed of the RGB and NIR bands is used as a base map. A shape file is created reflecting the location of the sensors in the field (Figure 8)



Figure 8. Location of sensors on the RGB-NIR map

The table that contains the location of the sensors is joined with the table containing the sensors measured parameters (Table1) by creating a new common field called "ID" and joining it with "field 1" in a one to one manner. This newly formed table (Table 2) is time enabled and saved as a layer file.

OB_I	Field1	Field2	Field3	Field4	ID	Date &Time	SM	Tem	EC
D								р	
1	sensor	434144	405209.	1627.82	1	9/1/2012	0.21695	18.9	0.09
	-10	9	1	5	0	0:00	9		6
2	sensor	434144	405209.	1627.82	1	9/1/2012	0.21714	18.8	0.09
	-10	9	1	5	0	1:00			6
3	sensor	434144	405209.	1627.82	1	9/1/2012	0.21690	18.7	0.09
	-10	9	1	5	0	2:00	4		5
4	sensor	434144	405209.	1627.82	1	9/1/2012	0.21685	18.6	0.09
	-10	9	1	5	0	3:00			5
5	sensor	434144	405209.	1627.82	1	9/1/2012	0.21714	18.5	0.09
	-10	9	1	5	0	4:00			5
6	sensor	434144	405209.	1627.82	1	9/1/2012	0.21657	18.4	0.09
	-10	9	1	5	0	5:00	7		5

Table 2: Time enabled table

Following that an empty folder called raster is created in the Geodatabase and we run the python script developed by Dr. Tarboton (Appendix 1). After creating a raster catalog in the assigned location iteration occurs and is represented in Figure 9



Figure 9. Iteration over time steps to reach IDW interpolation.

Following this step we adjust time display and time extend in the time slider tool to reflect our time step and we play the video. Snap shots of 09/18/2012 at 12:00 are represented in Figure 10. We notice from the snapshots the difference between the two crops in moisture retention, and soil temperature. Areas of high salinity are also highlighted. Visualization of our time series data is achieved.



Figure 10. IDW interpolation of (a) Temperature (b) Soil Moisture at 2 foot, (c) Soil Moisture at 1 feet, (d) Soil Electrical Conductivity

## 4.2 Objective two: Generating Maps.

The first step to achieve this goal was to create Vegetative Indices (VI) maps from the RGB-NIR image. VI maps aims to highlight a particular property of vegetation by a combination of surface reflectance at two or more wavelengths. In our study the following VI are used.

VI	Formula
NDVI	$\frac{R_{800} - R_{670}}{R_{800} + R_{670}}$
GNDVI	(NIR - GREEN) / (NIR + GREEN)
TCARI/OSAVI	$= \frac{3[(R_{700}-R_{670})-0.2(R_{700}-R_{550})(R_{700}/R_{670})]}{(1+0.16)(R_{800}-R_{670})/(R_{800}+R_{670}+0.16)}$
MCARI/OSAVI	$\frac{[(R_{700} - R_{670}) - 0.2(R_{700} - R_{550})](R_{700}/R_{670})}{(1 + 0.16)(R_{800} - R_{670})/(R_{800} + R_{670} + 0.16)}$
MSR	$\frac{(R_{800}/R_{670}) - 1}{\sqrt{(R_{800}/R_{670}) + 1}}$

Table 3: Vegetative Indices.

For each of these Indices a Model representing the formula was created and then ran in ERDAS imagine computing a Vegetative Indices map for each VI. Figure 11 shows the TCARI/OSAVI model and its corresponding map.



Figure 11 TCARI/OSAVI vegetative indices model (a) and map (b).

After computing all the VI maps, we stack these maps in GIS and using the

"identify" tool we record the corresponding pixel value in each of the VI maps (Table 4).

-1								
SAMPLE	PLANT:	CHLO.CONC.	SOIL:T.N	TCARI/	MCARI/	NDVI	MSR	GNDVI
NAME	TKN)	UMOLE/M2	(MG/KG)	OSAVI	OSAVI			
NW-1	13.27	503.52	14.124	14	1	0.535	1.55	0.353
NW-3	24.21	570.43	9.106	18	2	0.63	1.67	0.427
NW-5	13.89	596.91	87.829	15	1	0.55	1.71	0.4206
NW-8	10.71	639.89	50.884	16	1	0.58	1.71	0.437
NW-10	13.11	589.54	13.826	17	1	0.58	1.46	0.433
NW-12	12.31	616.13	9.523	18	2	0.64	1.91	0.4302
NW-14	10.20	642.87	7.900	21	2	0.68	2.02	0.449
NW-16	15.81	647.34	16.414	14	1	0.55	1.56	0.4192
NW-18	27.89	663.76	20.669	17	1	0.62	1.62	0.422
NW-20	19.98	642.87	52.330	16	1	0.59	1.59	0.3942
NW-22	15.03	577.77	10.338	17	1	0.6	1.77	0.409
NW-24	15.92	592.49	9.466	14	1	0.57	2.15	0.378

Table 4: A sample of data from Lab measurements and corresponding pixel value in VI maps.

LINEST function in EXCEL is then applied assuming that there exist a linear regression relationship between any of the lab measurements and these VI pixel values. The LINEST function is a complete linear least squares curve fitting routine that produces uncertainty estimates for the fit values. To evaluate the model built the  $r^2$  value is used; the r2 is computed using the following formula:

$$r^{2} = \frac{\text{regression ss}}{\text{total ss}} = \frac{\sum (\hat{y} - y_{av})^{2}}{\sum (y_{i} - y_{av})^{2}}$$

After running LINEST the following results were obtained:

Nitrogen plant and VI									
TCARI	MCARI	GNDVI	MSR	NDVI	MCARI/OSAVI	TCARI/OSAVI	b		
2.68	19.64	(68.48)	(5.31)	(9.66)	(0.88)	(0.96)	40.72		
2.55	26.49	28.75	6.16	7.92	5.66	2.13	9.78		
r <sup>2</sup> :0.52	5.71								
			Plant ch	lorophyll ai	nd VI				
TCARI	MCARI	GNDVI	MSR	NDVI	MCARI/OSAVI	TCARI/OSAVI	b		
34.87	-4.47	132.28	-40.02	75.31	-60.35	-7.11	458.37		
19.561	203.59	220.90	47.33	60.88	43.47	16.40	75.145		
r <sup>2</sup> 0.813	43.91								

soil nitrogen and VI									
TCARI	MCARI	GNDVI	MSR	NDVI	MCARI/OSAVI	TCARI/OSAVI	b		
0.545	64.40	102.65	-0.846	8.85	-12.43	-3.45	8.33		
8.726	90.83	98.55	21.11	27.16	19.39	7.31	33.52		
r <sup>2</sup> 0.176	19.59								

With an  $r^2$  of 0.813, a relationship between chlorophyll concentration and VI pixel value is computed as the following:

Chlorophyll Concentration micromole/m<sup>2</sup> = 34.8TCARI -4.47 MCARI+132.28GNDVI -40.02 MSR+75.31 NDVI -60.35MCARI/OSAVI -7.11 TCARI/OSAVI +458.37

All of the generated maps are then uploaded to GIS and using the Raster calculator tool the formula is inserted and a chlorophyll map representing the chlorophyll concentration over the whole field is calculated figure 12.



Figure 12 Chlorophyll Map of the field.

Doing that, we have generated a map that reflects the chlorophyll concentration or greenness of an area of 600\*300m from 25 known points. Knowing the importance of Nitrogen in the production function it would be of high importance to generate a similar map that can reflect the soil nitrogen in the field. Nevertheless the Nitrogen in the soil failed to find a linear relationship with the variables.

## 5. Conclusion

- GIS showed to posses tools that can help in Visualization & interpolation of time series data
- GIS tools related to image processing, Model makers, raster calculators etc...resulted in achieving a high resolution Chlorophyll map
- GIS is a tool to be used in precision agriculture

#### **References:**

APHA. 1998. Standard Methods for the Examination of Water and Wastewater, American Public Health Association, Washington, DC.

He, X.T., Mulvancy, R.L., Banwart, W.L. 1990. Rapid method for total nitrogen analysis using microwave digestion. Soil Sci. Soc. Am. J. 54: 1625-1629.

Mulvaney, R.L. 1996. Nitrogrn-inorganic forms. In Sparks ,D.L. (ed) Methods of soil analysis part chemical methods. Soil Sci Soc. Madison WI

http://resources.arcgis.com/en/help/

## Appendix 1

```
import arcpy, datetime, os
from arcpy import env
# Check out the ArcGIS Spatial Analyst extension for using the IDW interpolation tool
arcpy.CheckOutExtension("spatial")
env.workspace = r"C:\Users\Manal\Desktop\scipio data\Modelingwork"
gdbname="temp.gdb"
rascatname="rascat"
tptlayer="full table.lyr"
rasterfolder=r"C:\Users\Manal\Desktop\scipio data\Modelingwork\rasters"
intvar="TMPb1"
lyr = arcpy.mapping.Layer(tptlayer)
lyrTime = lyr.time
spatialRef = arcpy.Describe(lyr).spatialReference
startTime = lyrTime.startTime
endTime = lyrTime.endTime
timeExtent = endTime - startTime
timeStepInterval = lyrTime.timeStepInterval
iterations = timeExtent.days / timeStepInterval.interval
startTimeField = str(lyrTime.startTimeField)
arcpy.CreateRasterCatalog_management(gdbname, rascatname, spatialRef, spatialRef, "",
"0", "0", "0", "MANAGED", "")
rascatloc=gdbname + os.sep + rascatname
\mathbf{i} = \mathbf{0}
while i <= iterations:
   currentTime = str(startTime + (i*(timeStepInterval*24)+12))
  timeQuery = "\"" + startTimeField + "\"" + " = date "" + currentTime + ""
   tempFeatureLyr = "tempTimeLayer" + str(i)
   arcpv.MakeFeatureLaver management(lvr. tempFeatureLvr. timeOuerv)
   outRaster = rasterfolder + os.sep + "raster" + str(i)+".tif"
   print outRaster
   arcpy.gp.Idw sa(tempFeatureLyr, intvar, outRaster)
   arcpy.CalculateStatistics management(outRaster)
   arcpy.CopyRaster management (outRaster, rascatloc)
   i = i + 1
i=0
arcpy.AddField management(rascatloc, "datetime", "DATE")
with arcpy.da.UpdateCursor(rascatloc,["datetime"]) as cursor:
for row in cursor:
   row[0] = str(startTime + (i*(timeStepInterval*24)+12))
   i=i+1
   cursor.updateRow(row)
print "Done"
```