

Water Resource Management: Mapping of Current Land Use and Irrigated Agriculture Using Mutlitemporal Landsat Imagery

Jason San Souci, GISP, Executive Vice President & Chief Operating Officer, NCDC Imaging

State agencies, water providers and water users are constantly evaluating management of water resources in response to increases in population and demand, droughts, endangered species issues and reductions in Federal water program funding. A comprehensive decision support system (DSS) is being developed for each of the major river basins in Colorado. These will provide State of Colorado agencies, water users and managers a better means for organizing, accessing and evaluating a wide range of information and alternative strategies for managing their water resources. This, in turn, will help DSS users make informed decisions regarding major water issues and policy positions.

There have been major changes in land use and irrigation practices in each of Colorado's major river basins. An assessment of current irrigation water use, and changes in irrigation water use over the past 50 years, is needed by water users and water providers for water management purposes and for water rights administration by the State engineer. Such an assessment would address the following needs:

- Need of reliable mapping of current and historic land use and irrigated acreage by crop type
- Need to link irrigated areas with their sources of water supply. This will require mapping of ditch systems and well locations with their respective service areas.
- Need an assessment of major changes in land use and irrigation practices (i.e., changes in irrigated areas, transition to center pivot irrigation methods, and conversion of irrigation to municipal and industrial water use)
- Need of a system for mapping and analysis that is dynamic and efficient, fully documented, easily maintained and updated
- Need mapping of native vegetation category

NCDC Imaging utilized commercial image processing software and multitemporal Landsat satellite imagery to classify the crop type for each field parcel in the study area. County agricultural statistics was used as a reference. A limited but carefully selected set of ground information was also collected. The primary source of ground data was the Farm Service Agency's annual delineation of crop types provided by producers on high-resolution aerial photographs, which cover approximately 50 percent of farmlands in the study area. These FSA data was supplemented with data from ditch companies and irrigators. The goal of this data is to assist in making informed decisions regarding historic and future use of water.

Inputs:

1) Landsat TM (5 & 7) scenes over the AOI

Dates: 2000/04/05, 2000/05/23, 2000/05/31, 2000/06/16, 2000/07/18, 2000/07/26, 2000/09/12, 2000/10/14

- 2) Field Boundaries
- 3) Ground Verification Data

Methodology:

- 1) We have found that the best classifier for crops is to use corrected NDVI so that we can follow the phenologic progress of the fields and thus, unequivocally ID crops. We corrected each of the 8 Landsat scenes to yield an atmospherically resistant form of NDVI. The correction is designated NDVI* that scales the NVDI from 0 to 1 to match the potential range of vegetation. This calculation enables us to follow each crop through the season.
- 2) During the pre-classification effort, we georeferenced the digital raster graphic (DRG0 files to match the field boundaries provided by CWCB. This provided us with the base data that we needed to create the training data for each crop type. See Figure 1 below for an overview of the 3 georeferenced DRGs with the field boundaries overlaid onto the false-color Landsat NDVI* scene.



Figure 1: Georeferenced DRGs with CWCB-provided Field Boundaries and False-Color Landsat NDVI*

- 3) With the field boundaries, field verification DRGs and Landsat imagery now aligned, we selected the following breakdown of training samples (as entire fields) from the field boundaries polygon ESRI shapefile:
 - a. Alfalfa 37
 - b. Corn 24
 - c. Grass/Pasture 74
 - d. Dry Bean 3
 - e. Grain 3
 - f. Onion 2



As you can see, there is a significant difference in the number of training samples used in this classification. Ideally, we would have liked to see at least 10 dry bean, grain and vegetable training samples.

4) A spectral separability analysis was performed on these samples using the Transformed Divergence ("TD") method in ERDAS IMAGINE. TD values above 1700 indicate a good separation between classes and above 1900 indicate an excellent separation. Figure 2 illustrates the mean spectral signatures of the target crops and the TD separability.



Signature Separability Listing

Distance measure: Transformed Divergence

Best Average Separability

Bands			AVE	MIN	Class Pairs: 1: 2 1: 3 2: 5 2: 6 5: 6		1: 4 3: 4	1: 5 3: 5	1: 6 3: 6	2: 3 4: 5	2:4 4:6	
1 5 8	2 6	3 7	4	1859	1057	1057 2000 1960	1741 1999	1768 1997	2000 2000	1932 1967	1482 2000	1982 2000

Figure 2: Mean Crop Spectral Signature Plot and Transformed Divergence Separability Analysis Results

A quick evaluation of the TD separability would indicate that this classification should yield good results. Evaluating the NDVI scene and the TD results for Grass/Pasture versus Alfalfa showed that we would expect major confusion between these two classes (TD = 1057). We would also expect minor confusion between Alfalfa and Corn (TD = 1482).

5) We then ran a Maximum Likelihood supervised classification in ERDAS IMAGINE using these mean signatures above and the field boundaries as an area of interest. The resulting raster classification is illustrated in Figure 3.



Figure 3: Maximum Likelihood Supervised Classification Results

- Next we converted the raster classification into a vector shapefile using the Raster to Polygon tool in ArcToolbox. We simplified the polygons into simple shapes to reduce file size.
- 7) We intersected the vector classification shapefile with the field boundaries in order to generate area statistics by crop type for each field. We then summarized this shapefile by Parcel_ID to get a sum of crop acres for each field.

- 8) We then summarized by Parcel_ID again to get the maximum crop acreage for each field and calculated a maximum crop percentage of the total field acreage where, maximum crop percentage equals maximum crop acres divided by field acres.
- 9) In order to get to the final product of one field has one crop type, we joined the maximum crop type percentage shapefile with the field boundaries and removed duplicate attributes. The resulting shapefile also has a confidence attribute that was calculated using the MaxCropPct field. If the MaxCropPct was greater than 90%, then the confidence is 9. This means that more than 90% of the field is covered by a single crop classification. The scale goes down to zero, but these are fields that are outside of the Landsat image. Figure 4 shows an example of the resulting vector dataset with the associated attribute table.



FID	Shape	DIV	CAL_YEAR	PARCEL_ID	IRRIG_TYPE	ACRES	COMMENT	Class_name	Cnt_PARCEL	Max_CropAc	MaxCropPct	Confidence
6584	Polygon	4	2000	8487	UNKNOWN	2.677			0	0	0	C
6585	Polygon	4	2000	8522	FLOOD	70.802			0	0	0	C
1095	Polygon	4	2000	1859	FURROW	34.777		Grass_Pasture	25	6.280044	0.18058	1
3096	Polygon	4	2000	4125	UNKNOWN	2.614		DryBeans	11	0.484951	0.185521	1
3463	Polygon	4	2000	4682	FURROW	17.412		Alfalfa	30	3.153164	0.181091	1
3995	Polygon	4	2000	5343	FURROW	33.942		Onions	36	6.021664	0.17741	1
4264	Polygon	4	2000	5659	UNKNOWN	57.323		Alfalfa	62	8.283278	0.144502	1
4430	Polygon	4	2000	5834	FURROW	53.78		Grass_Pasture	45	10.181772	0.189323	1
4503	Polygon	4	2000	5910	FURROW	44.915		Alfalfa	55	4.720437	0.105097	1
4703	Polygon	4	2000	6153	FURROW	45.266		Corn	39	8.29409	0.18323	1
4718	Polygon	4	2000	6168	FURROW	23.095		Onions	24	4.327039	0.187358	1

Figure 4: Illustration of Final Results - Above: Resultant Vector Shapefile; Below: Associated Attribute Table