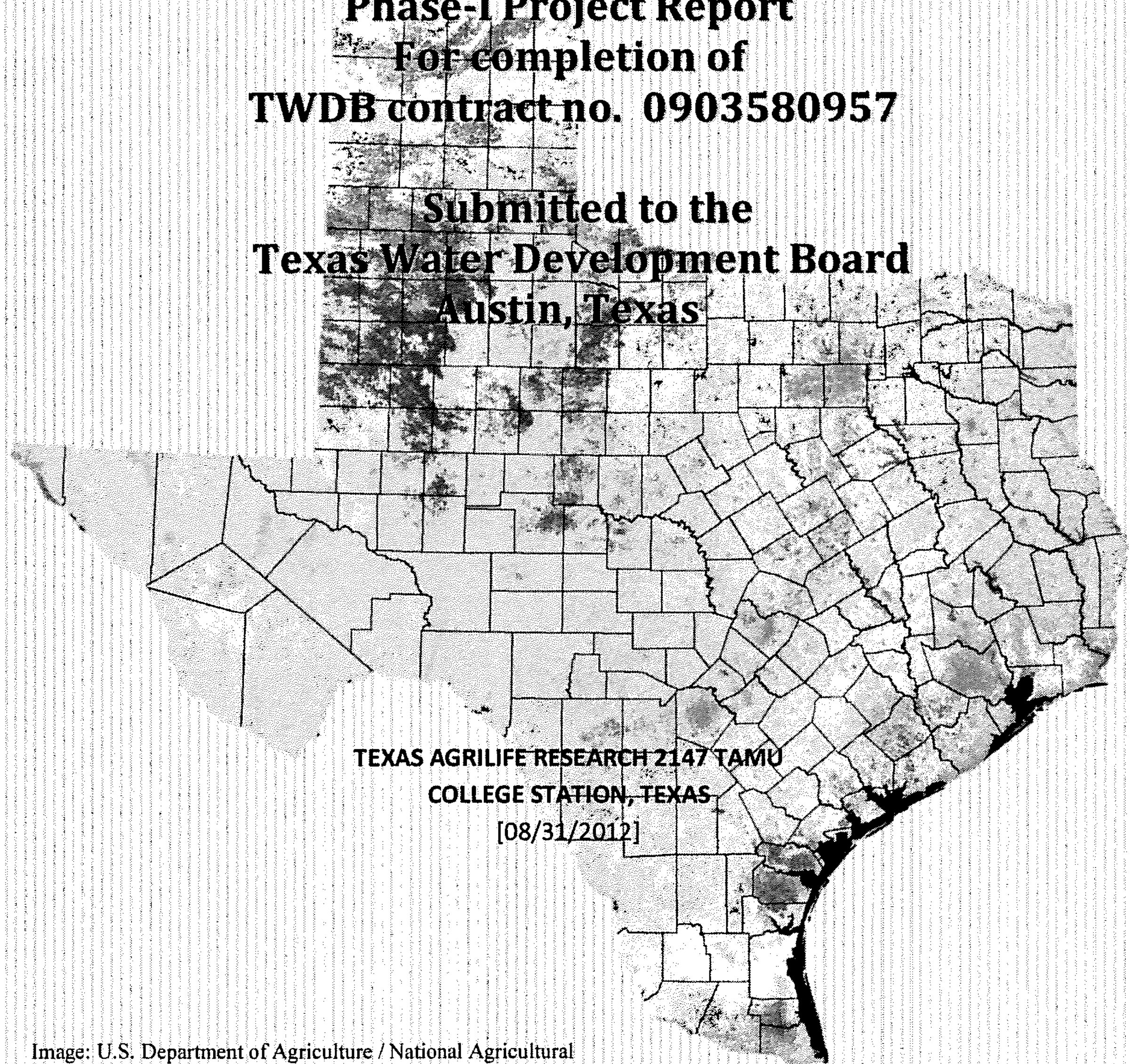
TEXAS A&M UNIVERSITY

Estimation of Irrigated Land-use using Time-Integrated Remotely Sensed Data

Phase-I Project Report
For completion of
TWDB contract no. 0903580957

Submitted to the
Texas Water Development Board
Austin, Texas



TEXAS AGRILIFE RESEARCH 2147 TAMU
COLLEGE STATION, TEXAS
[08/31/2012]

Image: U.S. Department of Agriculture / National Agricultural Statistics Service, 2010 Cropland Data Layer

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By

Texas AgriLife Research
2147 TAMU
College Station, Texas

Aug 31, 2012

Acknowledgements

The authors express their sincere thanks to Panhandle Groundwater Conservation District, Mesa Underground Water Conservation District and Farm Service Agency (FSA) particularly Bryan Crook of College Station Texas FSA for providing irrigated crop and planting data for Texas. We all wish to express our sincere gratitude to all the members of Texas Water Development Board, especially Cameron Turner for his support and guidance throughout the project. Finally, our sincere appreciation goes to all the individuals and staff members from spatial sciences laboratory without whom this project would have been possible.

Abbreviations

AVHRR	Advanced Very High Resolution Radiometers
CDL	Crop Data Layer
DOQQ	Digital Ortho Quarter Quads
DOSY	Day of Season Year
DOY	Day of Year
DT	Decision Tree
FSA	Farm Service Agency
GCP	Ground Control Points
GPS	Global Positioning System
GTP	Ground Truth Points
Megafile	Cleaned, Mosaicked and Stacked Time Series imagery
MODIS	Moderate Resolution Imaging Spectroradiometer
MRT	Modis Reprojection Tool
NAIP	National Agriculture Imagery Program
NASA	National Aeronautics and Space Administration
NASS	National Agriculture Statistics Service
NDVI	Normalized Difference Vegetation Index
NLCD	National Land Cover Dataset
PGCD	Panhandle Groundwater Conservation District
SPOT-VGT	Satellite Pour l'Observation de la Terre –Vegetation
TiSeG	Time-Series Generator
Time-series	Temporally ordered sequence of observations, usually measured in equal and discrete distances
Time-weighted	The inclusion of time into an analysis
Time-integrated	Gathering together chronological data into a workable dataset
TNRIS	Texas Natural Resources Information System
TWDB	Texas Water Development Board

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1 Executive Summary

This project was set forth by TWDB (Texas Water Development Board) to develop a consistent and scientific method for remotely delineating agricultural irrigated areas in Texas. The mapping of irrigated lands using remotely sensed data will serve two purposes. The first is to independently derive irrigated area statistics to contrast census and surveyed agricultural data. Second, to use the new area information at the county and sub county level will better aid in effective agricultural development and water resource management. Advice, data, knowledge and experience have been contributed by many state agencies, organizations and individuals as well as the collaborative effort of everyone, past and present, at the Spatial Sciences Laboratory at Texas A&M University.

In the first half of the project, Phase I, the mandate is to develop methodology for classification of 250 meter MODIS images into an irrigated area map of Texas using vegetation indices specifically NDVI (Normalized Difference Vegetation Index). In every process from beginning to end accuracy is of the utmost importance. Careful attention is paid to the spatial movement of pixels in the processing of the MODIS images. To ensure the quality of ground control points and accompanying signatures that the classifications are built upon, each GCP is centered on every associated field and rating for field size was performed. The use of multiple classification decision trees, in parallel, to boost overall accuracy is implemented and finally an agricultural mask is applied to insure the overall correctness.

In the current 2010 analysis the coastal regions are areas of concern. The reason for this is the greater than average rain fall amount during the 2010 growing season and field data collection practices in the first area visited for the project. For 2011, the ground truth dataset also has potential issues in all surveyed areas because of the record setting dry weather that occurred in Texas. Both years of ground truth data represent outliers to normal weather patterns. Addition of ground truth data, to the current datasets, for a growing season under normal weather conditions is needed.

Confidence in the remaining two areas of the state examined in the Phase I of the project, the Panhandle and Winter Garden regions, for 2010 is high. The execution of the projects methodology in these locations shows the validity of the processes. Automation and future implementation is achievable.

With phase II accuracy of the irrigated area classification will be further improved by several means. First the exploration into the modification of the methodology for coastal region will provide the highest accuracy possible. Using information from signature analysis, temperature data, and multi-year planting data information classification regions will be created to improve the accuracy distribution. Finally the integration of nexrad precipitation data will inform the model of weather conditions during the growing season allowing for better interpretation of NDVI signatures.

The completion of phase II will incorporate current methodologies and practices along with accuracy enhancements into a comprehensive adjustable automated model. This model will render information about the amount of irrigated acres in Texas. The future benefits of this project, with additional funding, will aid TWDB in management plans for water use estimates at a sub county level and inputs into complex environmental models.

2 Introduction and Background

Irrigation is extremely important in high production agriculture; irrigations ability to remove some of the variability from crop production in non-ideal conditions is invaluable. In the contiguous United States only18.3 percent of harvested croplands are from irrigation but account for nearly 50 percent of the value of all crops sold (Pervez and Brown, 2010). Fresh surface water is the major source for irrigation, globally about 72 percent of freshwater is being used for agricultural purposes, and north and Central America alone account for 49 percent of freshwater withdrawals (Postel and others, 1996). In the year 2005, Texas was one among the five states for major fresh water usage in USA (Kenny and others, 2009).

The ability to quantify irrigated areas helps in the understanding of water use both agricultural and nonagricultural (Thenkabail and others, 2005). Results of irrigated areas quantification can be used for modeling of water exchange between the land surface and atmosphere, (Giordano, 2002; Boucher and others, 2004; Ozdogan and Woodcock, 2006), analyzes of the impact of climate change and variability on irrigation water (Vorosmarty, 2000; Alcamo and others, 2003; Rosenzweig, 2004), and management of limited water resources that affect global food security (Vorosmarty, 2005). Irrigated maps provide important information on water usage, eventually helping planners, policy makers, researchers and decision makers.

Studies have been using different types of satellite imaging sensors to account for irrigated areas as they are cost effective, accurate and repeatable. Global irrigated maps are created mainly using Satellite Pour l'Observation de la Terre –Vegetation (SPOT-VGT) and Advanced very high resolution radiometers (AVHRR) sensors (DeFries and others, 1995; Loveland and others, 2000; Biradar and others, 2009; Thenkabail and others, 2009). Although multiple global irrigated cropland classification efforts have mapped national and regional level irrigated croplands, they were derived from remotely sensed images of coarse resolution (10km-1km) sensors. These sensors have some limitations with spatial and temporal resolutions and data quality (Wardlow and Egbert, 2008). These studies lacked the detail necessary for an accurate sub-county level classification needed for future models and detailed management plans. A detailed map of irrigated land cover over larger area is essential. Moderate Resolution Imaging

Spectroradiometer (MODIS) sensors are promising as they have unique combination of spatial, spectral and temporal resolutions ((Lobell and Asner, 2004; Mingwei and others, 2008; Wardlow and Egbert, 2008). Many studies have been using MODIS-NDVI images for cropland classifications (Thenkabail and others, 2005; Wardlow and Egbert, 2005; Biggs and others, 2006; Colditz and others, 2007; Fritz and others, 2008; Mingwei and others, 2008; Ozdogan and Gutman, 2008; Ren and others, 2008; Boschetti and others, 2009; Funk and Budde, 2009; Dheeravath and others, 2010; Gumma and others, 2011) Using MODIS-NDVI time series data is advantageous, it saves storage space, requires less processing time and provides simple classification over complex landscapes (Biggs and others, 2006).

In order to generate time series irrigated maps different types of methods are used. The common methods are unsupervised classification, (Biggs and others, 2006; Gumma and others, 2011) supervised classification (Fritz and others, 2008), spectral matching techniques (Lobell and Asner, 2004; Colditz and others, 2007; Dheeravath and others, 2010), decision tree classification (Wardlow and Egbert, 2005; Ozdogan and Gutman, 2008) and combination of the above mentioned techniques (Thenkabail and others ,2005).There is a need for consistent comprehensive, unbiased method which can be used on a repeatable basis and replicated in multiple areas to quantify irrigated croplands.

In this report, we describe our methods and various steps involved to classify irrigated lands. The first objective was to develop cloud-free imageries of high temporal resolution MODIS Products. This was achieved by modifying a preexisting MODIS_NDVI product using TiSeG (Time-series generator) program described in detail in data processing and analysis. Though the MODIS –NDVI product is made robust for enhanced vegetation sensitivity and is accurate in radiometric, geometric and atmospheric correction this product also provides pixel-level quality information(NASA) that is used by TiSeG to further improve the data. Scientists involved in irrigated area mapping using MODIS data in South Africa (Colditz and others, 2007), Mexico and Southern Great Plains (Lobell and Asner, 2004) took advantage of this information to clean MODIS-NDVI products to eliminate low quality pixels obscured by clouds, shadows and other quality issues, which minimized noise in the imagery. Second objective is to develop a methodology to estimate irrigated agricultural lands using up-to-date image analyses techniques and statistical methods. Our team explored various techniques and methods to classify irrigated lands and decided spectral matching with supervised decision tree classification as the best method. As part of methodology described in detail, the use of decision tree classification is recognized to be an accurate approach for mapping irrigated areas (Friedl and others, 2002; Homer and others, 2004; Wardlow and Egbert, 2005). Finally estimating irrigated acreages by county can be seen in our results section. The current methods were adopted keeping in mind our goal towards automating the procedures of Phase I to quantify irrigated croplands for the entire state of Texas.

3 Methodology

3.1 Data Acquisition

3.11 Downloaded and requested

A classified map that we used for reference and accuracy improvement was the crop data layer (CDL). An improvement over the national land cover database (NLCD) map the CDL takes the agricultural area inside the NLCD and breaks it up into its individual agricultural components an example of two of those components would be corn and aquaculture. The 2010 and other CDLs were acquired through "Data Gateway" http://datagateway.nrcs.usda.gov/. The CDL is used in the generation of an agricultural land (ag) mask and a reference to field data.

Through a freedom of information request to the Farm service agency planting data from 1996 through 2010 was acquired at a County resolution for crop type, acreage planted and irrigation practice. This data is collected voluntarily by the FSA from farmers on an annual basis and 1996 was the earliest data available in a digital form with the components required for analysis. The FSA data will be used for creating like areas of classification and for further refinement of the ag land mask.

Used to double check the FSA planting data for errors the National Agriculture Statistics Service (NASS) census harvest data an independent data set from 1997, 2002 and 2007 was used to compare against the aggregated FSA totals. Acquisition of the NASS data was from the NASS website interface called "Quick Stats" http://quickstats.nass.usda.gov/ where data can be selected and downloaded in spreadsheet form.

The imagery used for this project from the onset has been laded out to be from the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor on the TERRA satellite platform. Initially collaboration between the Center for Space Research at University of Texas and the Spatial Sciences Laboratory at Texas A&M University was planned to create daily time-weighted rolling cloud-free imageries from raw MODIS image Swaths. Swath Images were quickly abandoned in-favor of tiled products available through data Pool "https://lpdaac.usgs.gov/get_data/data_pool NASA's FTP site that when using FileZilla, a free FTP download manager available at http://filezilla-project.org/, that made downloading quick and easy. This was done for two reasons, the first was the ability to download image products directly from Data Pool, meaning ease of image accusation without the need to go through the Center for Space Research and second cleaning of noise from the datasets has been done for some of the products available as well as generation of indices such as Normalized Difference Vegetation Index (NDVI). Pre-prepared product explored were MOD09GQ a daily, tiled, 250m resolution of Red and Near Infrared images as well as MOD09Q1 an 8 Day composite, tiled, 250m resolution of Red and Near Infrared images. The MODIS product that is currently being employed in the project is MOD13Q1 (This product is generated by NASA using the daily MODIS Level-2G (L2G) surface reflectance, pointer file, geo-angle file and 1-km state file) this product has calculated vegetation indices based on a 16 day composite meaning that need for calculating NDVI in the lab has been eliminated and most noise due to sensor errors, sensor angles and cloud contamination has been removed. Only products in the 250m resolution is used because of the incense in the likely hood of detection of crop fields with resolution of 250m (Lobell and Asner, 2004; Ozdogan and Woodcock, 2006).

The Texas Natural Resource Information System better known as TNRIS http://www.tnris.org is a rich source for freely available geographic information. High-resolution imagery in the form of Digital Ortho Quadrangle (DOQQ) and countywide mosaics were acquired in order to aid in the refinement of GPS points and the understanding of our given study areas. The other very important data set acquired from TNRIS was a statewide shape file of all the counties in Texas

3.12 Partner contributed data

Thanks to the help of TWDB to opening the lines of collaboration to Mesa Underground Water Conservation District and Panhandle Groundwater Conservation District Irrigation meter data for 2011 and 2010 respectively was made available. This meter data can be used to reference the results of the finished irrigated non-irrigated classified image. Unfortunately only the correctness of irrigated areas can be checked with this meter data.

3.13 Ground truth information

Ground control points (GCPs) were collected during the summers of 2010 and 2011 by employees of the SSL lab. Over the two years five areas were visited Cameron, Jefferson, Plainview, Uvalde, and Wharton counties (Appendix A). These counties were selected in consultation with TWDB. Not all counties were visited both years. Surveyors in the field were required to make educated observations in the identification of crop type and irrigation practice on fields estimated to be large enough to be detected. Field size more than 120 acres of crop type were selected for GCP collection, these criteria was set keeping in mind delineation of irrigated lands using MODIS 250m data. Once an appropriate field for crop type, irrigation method and size was located operators would collect the GPS positions. In order to keep the GPS points off of roads and into fields the field technician would offset the GPS location at least 30 m into the appropriate field This 30 m projection was done to aid in the post processing of the GPS data.

Table 3-1: Number of GCPs collected in each location

County	# of GCPs collected	
	2010	**2011**
Cameron	344	185
Jefferson	Not Visited	17
Plainview	150	Not Visited
Uvalde	160	182
Wharton	126	95
Total	780	479

Due to the nature of how the ground truth data points were collected it is necessary to alter their location to improve the usefulness of the signatures. Using high-resolution imagery and a classified image called the Crop Data Layer (CDL); the entire field collected ground truth data points were manually moved into the center of the fields by technicians at the spatial science lab at A&M. The above mentioned process was carried out for field structure only not for crop type.

A shape file of multiple ring buffers with the radii is corresponding to multiples of the MODIS pixels resolution are also used to aid in the positioning of the final points. Each moved ground truth point was also rated from 0 to 3 for the number of rings that a given field, that had the ground truth point in it, could contain. These ratings were used to exclude ground truth data points from the signal extraction process.

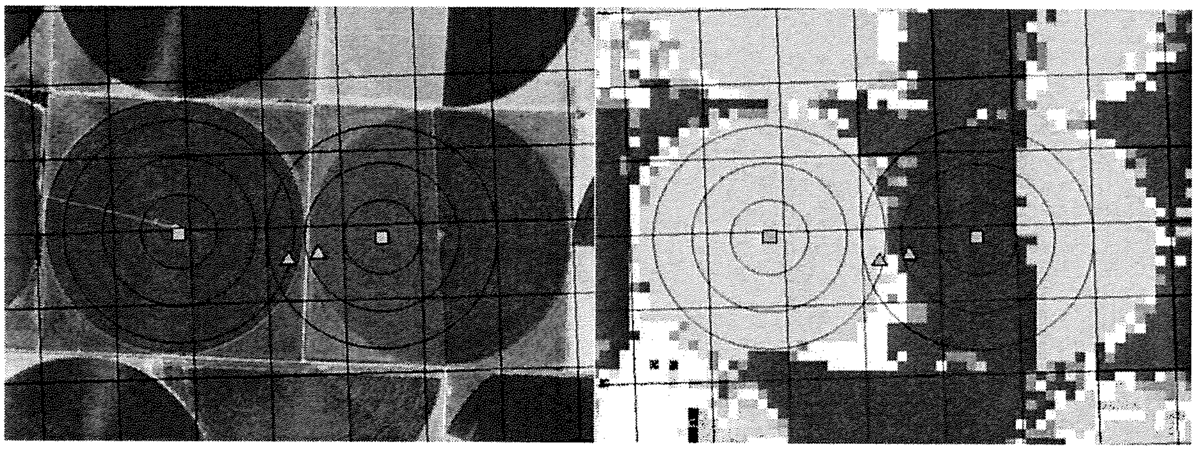


Figure3-1: An example of positioning GCPs: These images displayed the movement of the ground truth data points overlaid on the high resolution imagery (left) and the classified CDL image (right). The triangles represent the original location of the two points displayed in the above images and the squares are on the relocated positions. The grid on both images is a visual representation of the size and orientation of the pixels in a MODIS image.

3.2 Data Processing and Analysis

3.21 MODIS data

The Downloaded Modis images from Data Pool have a Sinusoidal projection that needs reprojected into the NAD83_Albers project projection. This is done using the MODIS Reprojection tool that is provided free of charge by NASA with a free registration found here https://lpdaac.usgs.gov/tools/modis_reprojection_tool/. Able to operate in both manual and batch mode the MODIS Reprojection tool can spectrally and spatially subset and or mosaic the MODIS data into a format that is useful for the next stage in the processing specifically"HDF data". If the outputs from the tool need to be used immediately in Arcmap for visualization then the imagery should be output into geotiffs for better compatibility

USA Contiguous Albers Equal Area Conic USGS

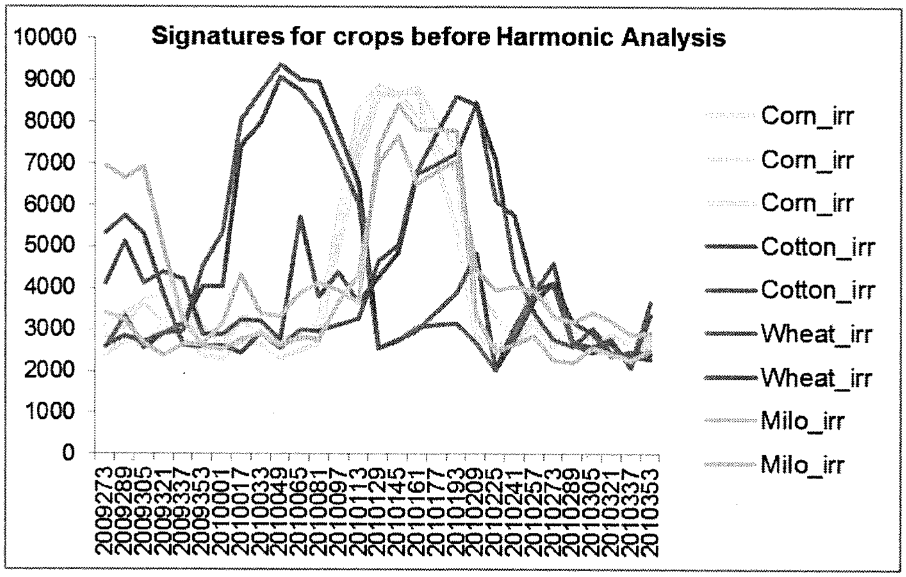
Projection: Albers
False_Easting: 0.000000
False_Northing: 0.000000
Central_Meridian: -96.000000
Standard_Parallel_1: 29.500000
Standard_Parallel_2: 45.500000
Latitude_Of_Origin: 23.000000
Linear Unit: Meter (1.000000)

Geographic Coordinate System: GCS_North_American_1983
Angular Unit: Degree (0.0174532925199432955)
Prime Meridian: Greenwich (0.000000000000000000)
Datum: D_North_American_1983
Spheroid: GRS_1980
Semimajor Axis: 6378137.000000000000000000
Semiminor Axis: 6356752.314140356100000000
Inverse Flattening: 298.257222101000020000

Figure3-2: Project projection

Once the MODIS images have been subset and reprojected into an ".HDF" file format with the correct projection a software tool that runs on an IDL Virtual Machine named Time-series Generator (TiSeG) is used for noise removal from images, layer stacking and harmonic analysis. TiSeG can be acquired by contacting the programs author (Colditz and others, 2008).

MODIS_NDVI products contain data quality layers called "assessment science data set' (QA-SDS), this layer indicates possible contamination due to clouds, aerosol or shadows at pixel level. TiSeG helps to analyze and visualize the quality information and identify number of invalid pixels for the times series imagery and calculate the length of gaps created by the invalid pixels. Then interpolating through the low quality pixel gaps is the first step in removing noise from the imagery. The second operation in the TiSeG environment is the execution of a harmonic analysis to smooth time-series (figure3-3).Harmonic analysis is a representation of a wave with large complexity and noise into a simple summation of sine and cosine waves with different frequencies, amplitudes and phase angles. More details on the software and harmonic algorithm can be found by referring to (Roerink and others, 2000; Colditz and others, 2008) .The final product that comes out of the TiSeG program is the smoothed MODIS-NDVI high-quality noise free imageries that from now on is referred to as the megafile. This megafile (stacked and mosaicked MODIS-NDVI high-quality noise free imageries) will be used with the ground truth points for signature extraction and input to the decision tree classifier.



Example of Signatures before interpolation

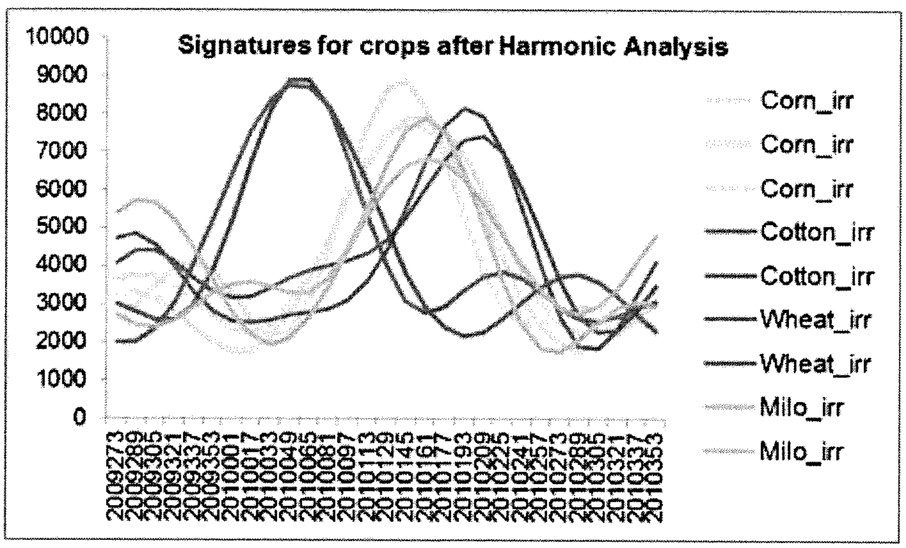


Figure 3-3: Example of Signatures before (top) after (bottom) Harmonic Analysis; large noise reduction

3.22 Creating ROI based on ground truth locations

The shape file containing the ground truth locations (GTL) with good rated points were imported to ERDAS Imagine 2011. A new area of interest (AOI) file was created and attributes from the GTL's were exported to AOI. From the newly created AOI the spectral signatures were extracted using signature editor tool from ERDAS Imagine 2011 software. Extracted spectral signatures were plotted using excel to visualize the NDVI response to irrigation in the peak growing as well as irrigation months based on crop types. After all best signatures were extracted from the final megafile; they were shifted by each crop type based on the portion of the state being investigated. The shift in this signature across different counties/regions in the state is being investigated because of the variations in the planting-harvesting dates (and in turn the growing season) in response to the variation in weather across the state. Shifting is part of methodology to develop a master signature database for building decision trees, which can later on be used for classification. The shift of NDVI signatures in figure 3-4 illustrates how signatures from one area can be adapted to match signatures from another through a simple shift.

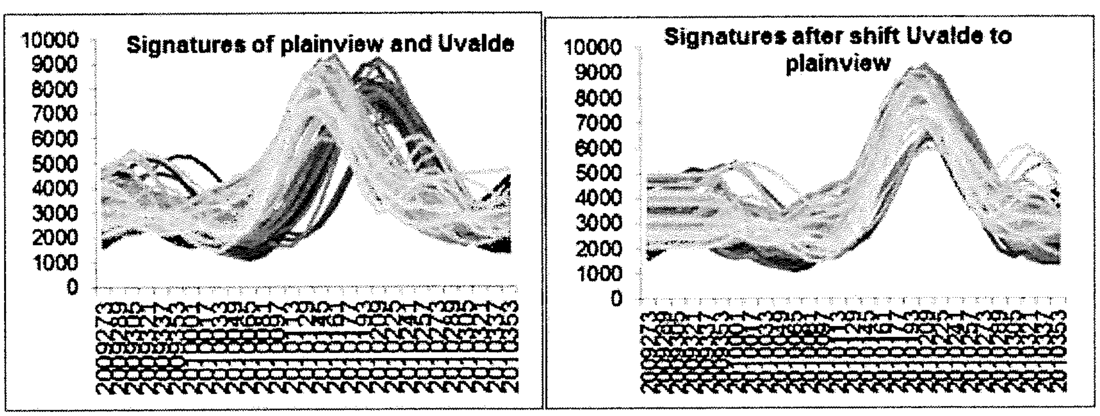


Figure 3-4: An example of shift in signatures from Plainview to Uvalde for a certain crop type.

3.23 Producing See5 decision trees

To produce time-series irrigated map for Texas, a supervised, decision tree (DT) classification algorithm (See5) was applied on MODIS 250-m NDVI data. DT classifiers offer numerous advantages over regular classifiers, 1.Ability to handle large volumes of data, 2. Efficient and accurate in interpreting classification due to advanced options of pruning and boosting, 3.Ability to manage non-linear, hierarchical relationships between predicted and predictor variables (Wardlow and Egbert, 2008). Time-series MODIS NDVI data exhibited intra-class variations, bi-modal distributions for a given crop type, this may be due to discrepancies in climate and management practices (Wardlow and others, 2007). DTs non-parametric nature can operate on thresholds in multi-spectral space rather than measures of central tendency or normality, thus can handle multimodal distributions (Hansen and others, 1996).

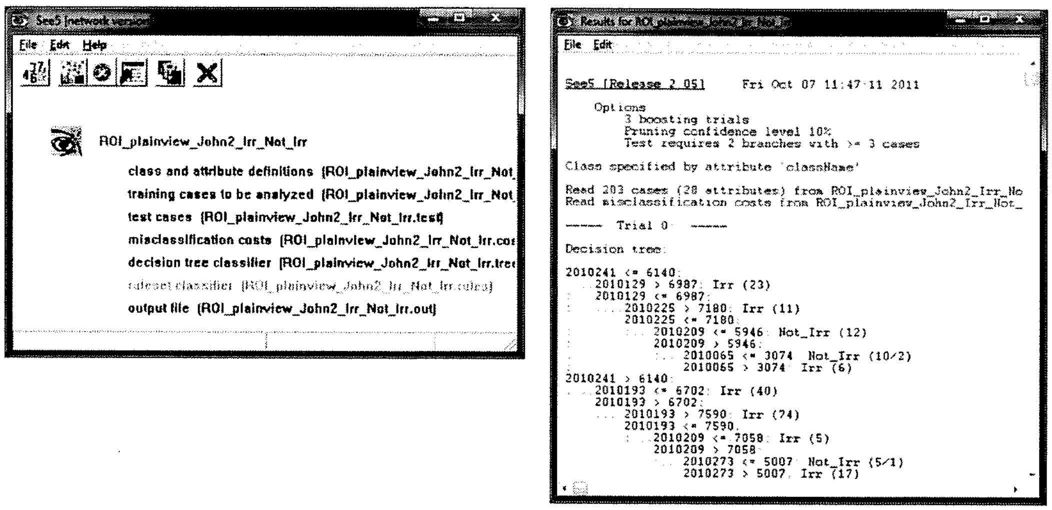


Figure 3-5: An example of See5 Decsion tree builder and out put file from see5

Using the NDVI signatures extracted from the mega file, the data files were created following the guidelines of See5: An Informal Tutorial (http://rulequest.com/see5-win.html#files, accessed July 6th, 2012) to construct DTs. The 'name', 'case', 'test', and 'data' files generated for see5 were imported to see5 program. See5's boosting algorithm, set to three trials and 25 % global pruning was preferred to build DTs based on literature for best positive results (Quinlan, 1996; Boryan and others, 2011); figure 3-5, shows an abstract of the working software and the output file.

In order to generate the test files for see5, 68 percent of data values in the data set were considered by calculating the average and standard deviation for each crop type and computing plus/minus one standard deviation from average values.

3.24 Classification

The ".out" file generated from see5 was used to build DTs in ERDAS for each trial with the help of knowledge engineer tool. Decision trees were built on constructing a rule-based hypothesis for each trial (Pouncey and others, 1999). The constructed DTs for each trial were then used to classify the mega file of Texas, figure 3-6 provides example of DTs produced in ERDAS. The three classified maps for the given area of Texas generated from the three trials are then combined with the help of raster calculator to generate one classified map that has higher accuracy than any of the three maps that were combined into it.

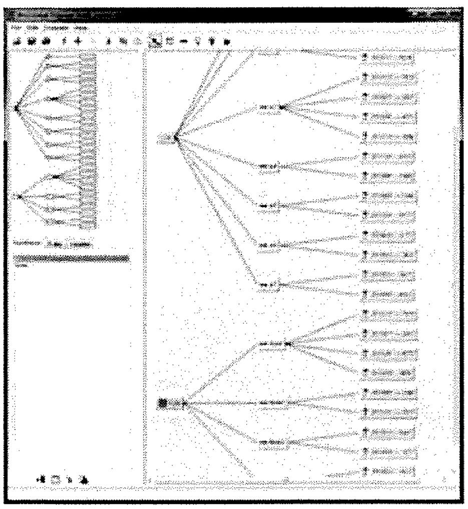


Figure 3-6: example of Uvalde decision tree.

The conditions to combine the three classified DT generated maps use nested statements of if-then conditions in Arcmap10. The if-then statements are looking for agreement between the three images, because there are only three images any agreement at all mean majority wins and the class type is set for a given pixel. In the event of total disagreement between the three classified images the class type is assigned base on which classified image that was generated from the DT with the highest accuracy from the test data in See5.

3.25 Masking them based on AG lands and irrigated and non-irrigated areas for Texas

The Crop Data Layer (CDL) is an annual product that is a refinement of the National Land Cover Dataset (NLCD). Expanding the NLCD to include crop types the CDL increases the land cover information and usefulness on an annual basis. The reason the CDL is being used for creation of an agricultural mask is because of its annual update and release.

Transformation of CDL into an agricultural land mask is done by first selecting desirable classes from undesirable classes within the classified CDL image. For example, desirable values such as corn, cotton and wheat would be reclassified into the value 1 and undesirable values such as evergreen forest, open water and any developed space would be reclassified to the value of 0. The result is a binary classified image of area for classification and area to be disregarded at the resolution of the CDL. Aggregation of the classes is done so there is no conflict between classes, during the resampling process, in the same binary group. The reclassified CDL image is then resampled and aligned to the native MODIS resolution project imagery keeping the mode value under the newly resampled pixel.

CDL over Hale County | Image 30m Ag lands Mask | MODIS resolution Ag lands

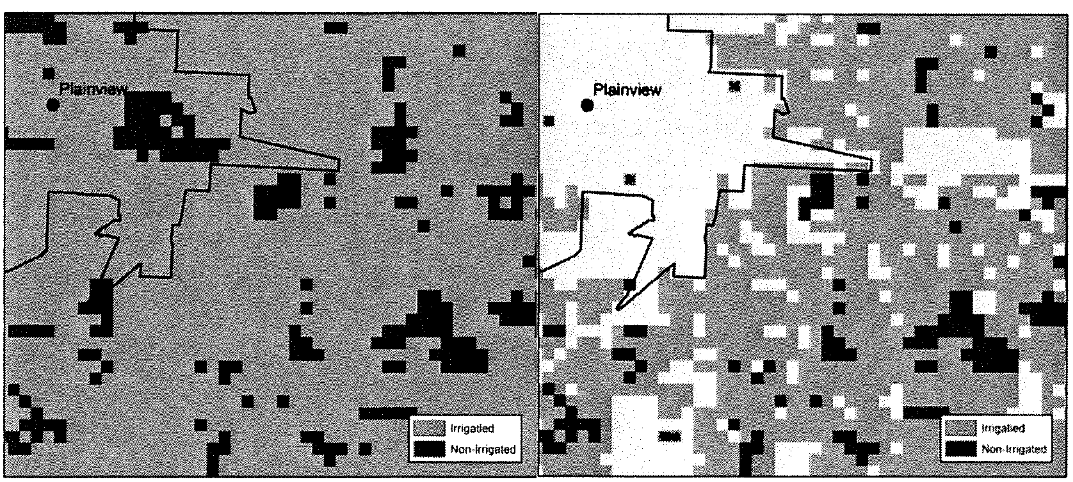


Figure 3-7: Classified image in Hale County Before (left) & after (right) application of the Ag Lands Mask Green is classified as irrigated and brown is non-irrigated.

4 Results

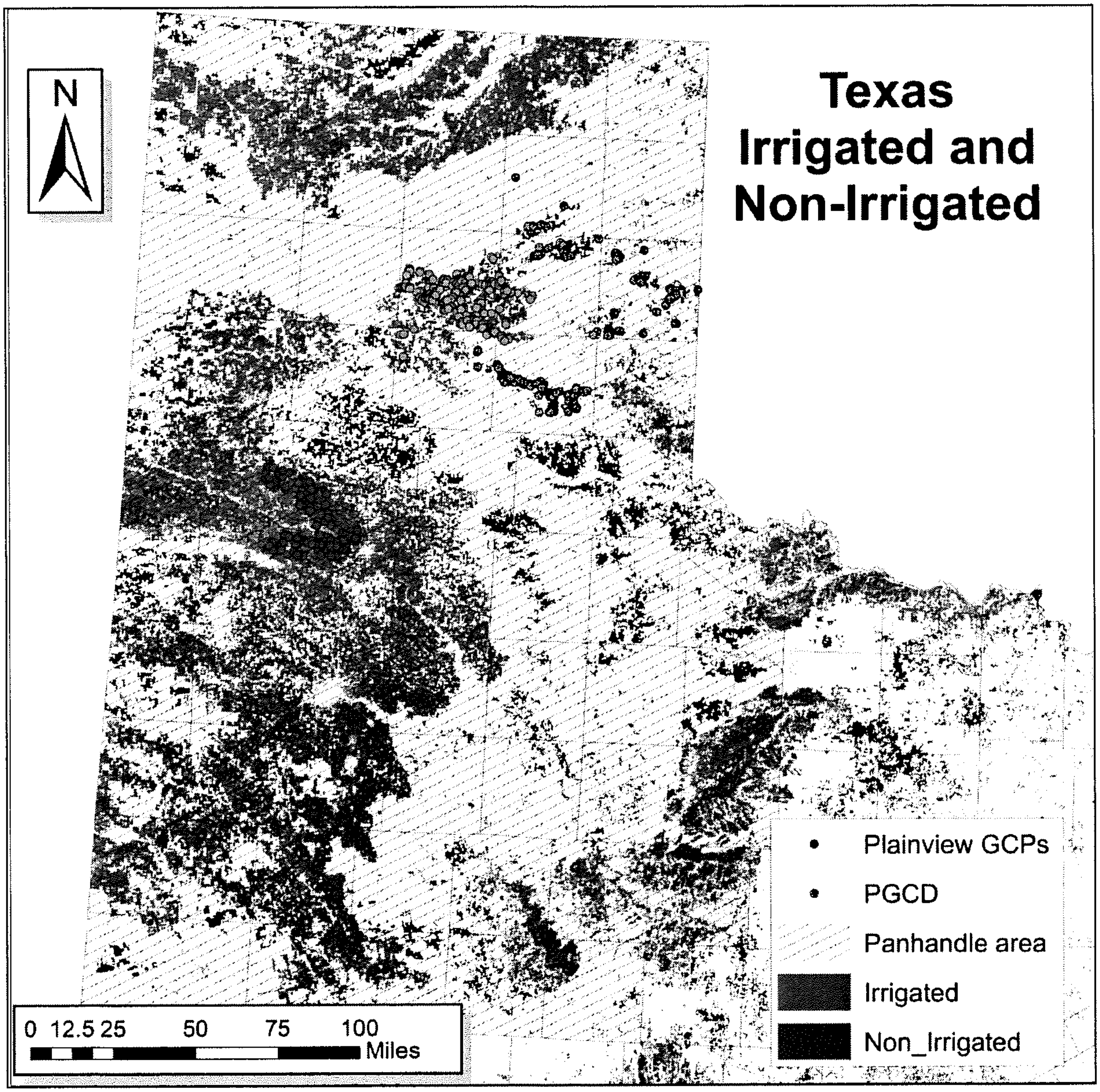


Figure 4-1: Map of Panhandle classification

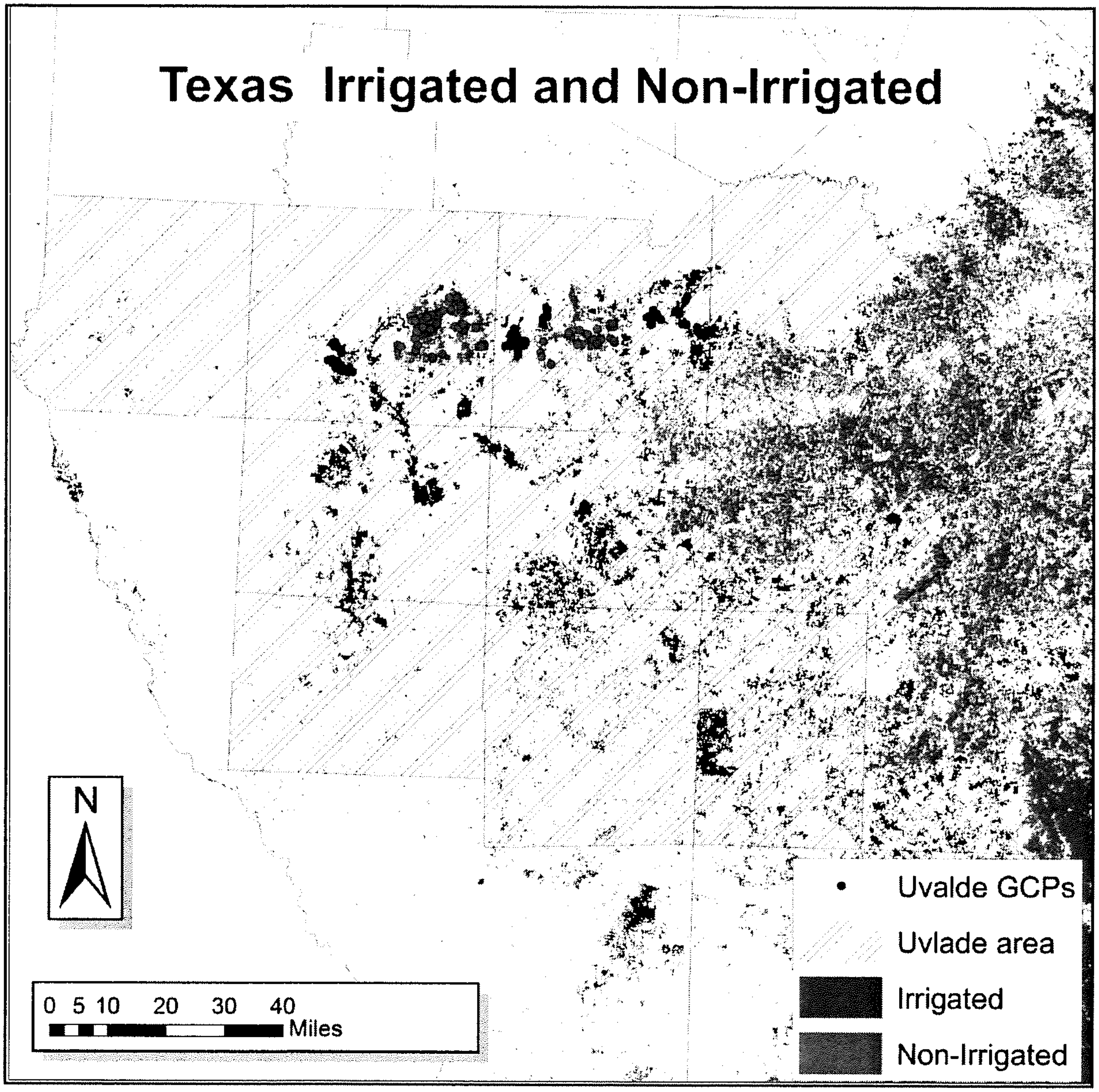


Figure 4-2: Map of Uvalde classification

4.1 Refinement of FSA Data

USDA-FSA (Farm Service Agency) planting data was acquired initially from Bryan Crook of FSA in College Station Texas for 2010 and then again through a freedom of information act request to FSA for planting data information from 1996 through 2010. The data consisted of multiple entries for every crop, for every county and every year listing the acreage planted and the irrigation practice used. Before the raw data could be useful, a lengthy refinement process had to be undertaken. First of all, dates outside of each growing season were removed. For wheat and oats acceptable dates fell between August and the end of April. All other crops were restricted between January and the end of September. Next, any entry below 5 acres was removed because large row crop fields are the main point of study and 5 acres was concluded to be too small to be included. Then, any county whose total reported cropland area fell below .01% of the total reported planted area in Texas was excluded. For any crop type inside a county, a threshold was set so that if a crop type fell below 1% of the total reported planted acres of county it would be removed. Once the initial refinement was complete, any crop type per county that has lower than 67 entries over the 15 year span was deleted from the data set. The 67 entries sample group size was derived statistically from a large population with a confidence level of 90% and a confidence interval of 10%.

Upon examination of the refined FSA data a major error was discovered in the dataset. From 1996 through most of the data in 2009, rice which is an exclusively irrigated crop was listed as non-irrigated. This error was corrected and the analysis continued.

For examination of planting data standard day/month/year dates are not easy to use especially for growing seasons that span multiple years, like in wheat, or when deriving an average between years. For example in a spread sheet program when you average 1/1/10 and 1/3/09 the answer is 7/3/09. To fix this issue many studies use Julian days or DOY (day of the year) values, but because a growing season can span multiple years a new value had to be created. This new value is called DOSY (day of season year). The difference between DOY and DOSY is that valid DOSY values can range from -364 through 365 allowing for the capture of the full growing season and the ease of analysis between growing seasons.

The main purpose of this analysis of FSA data is to use planting dates as a means of breaking Texas into groups of counties with similar growing seasons to aid in classification. This sorting was accomplished by finding a mode range of planting dates for every crop in every county.

After consulting with Dr. Prasad Daggupati, a Visual Basic program in Excel was used to accomplish this.

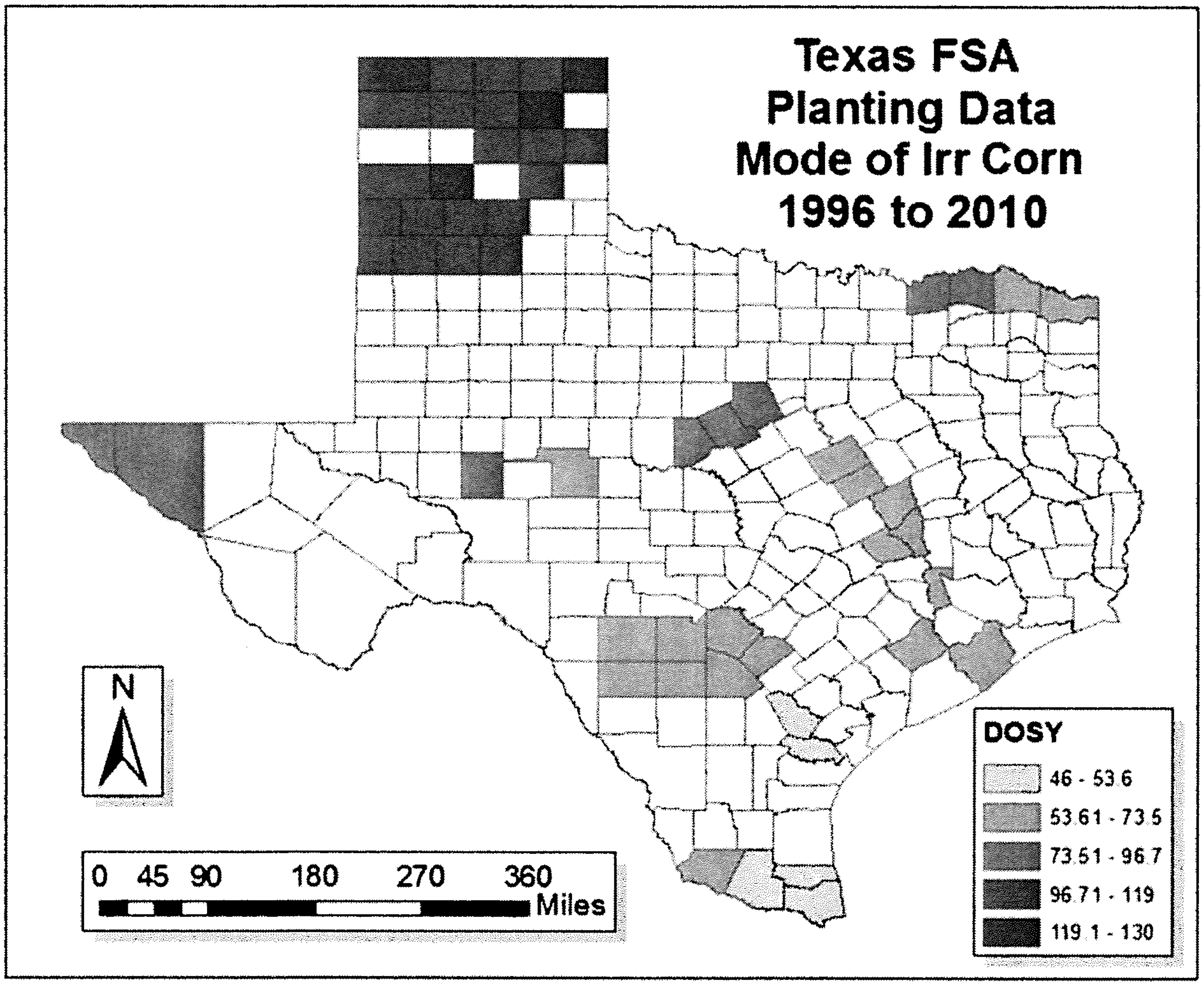


Figure 4-3: Distribution of average mode planting dates for irrigated Corn ranging from DOSY 46 that is in mid-February to DOSY 130 in mid-May.

While useful for the rest of the study the usefulness of the FSA data to enhance the final classification was not immediately apparent. Until all 15 years of the FSA dataset was aggregated by counties containing only non-irrigated crops, only irrigated crops, both irrigated and non-irrigated crops, and no selected agriculture presence. Row crops included in this final summation include corn, cotton, sorghum, wheat, rice, oats, peanuts and soybeans.

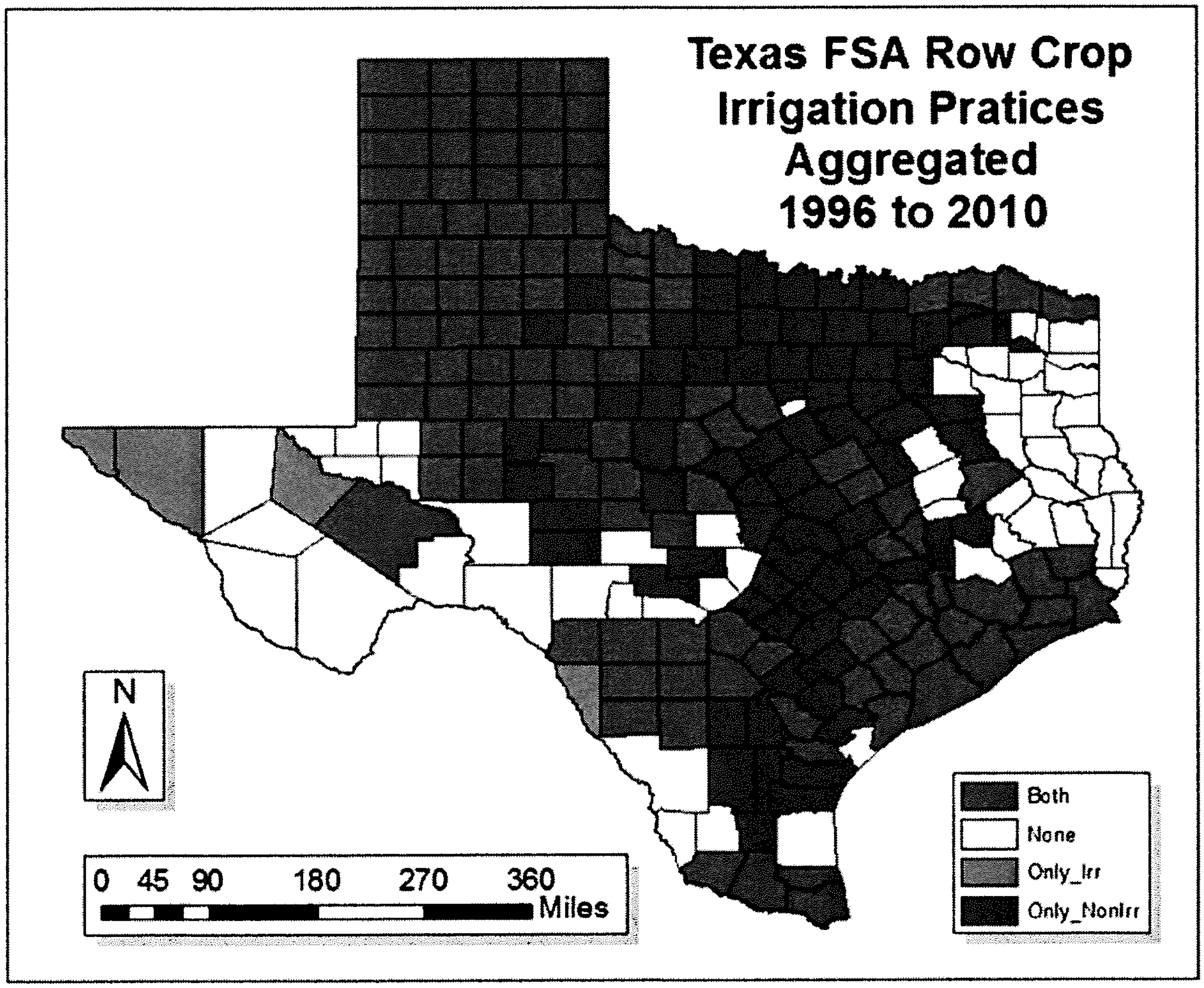


Figure 4-4: Distribution and type of Irrigation for row crop agriculture

This information can then be incorporated in the current agriculture land mask and classification process. The agriculture land mask can be refined further by excluding all counties with no reported desired row crops for the 15 year span of time. Also, areas of absolute total irrigation and absolute non-irrigation can be automatically assigned classes leaving only areas where both irrigation practices are present for classification.

The Addition of the FSA data to the existing agricultural lands mask and the end classification can only increase the overall accuracy and correctness of the final product meaning potential for environmental models with increased accuracy and management decisions with better understanding.

4.2 Validation of CDL dataset

Table 4-1 GCPs to CDL comparison by crop

	Correct	Total	Percent
GCPs Raw	446	627	71.1%
GCPs Clean	274	347	**79.0%**

This is a validation of the CDL using the GCPs for comparison. The cleaned GCPs to CDL showed 79 percent accuracy of crop type Table 4-1, showing the usefulness of the CDL as a source of crop type and location. A detailed comparison of GCPs to CDL based on crop types can be seen appendix C.

4.3 Validation of masking using Ground Control Points and Ground Truth Points

Table 4-2: Overall classification accuracy after masking

	Out of mask	In mask	Total	% correct
Plainview	9	75	84	89.3
Uvalde	3	88	91	96.7
Wharton	9	89	98	90.8
Cameron	5	69	74	93.2
PHGD GTPs	13	306	319	95.9
Total				**93.2**

When the generated aglands mask was compared to the cleaned GCPs , which were used in see5 to build decision trees for classification, and partner contributed GTPs there was high accuracy of points locating within the mask. All the points both GCPs and GTPs were collected without concern or knowledge of the aglands mask. The overall accuracy of the aglands mask was 93.2 percent, Table 4-2. The use of agricultural mask improves accuracy and helps to eliminate non-agricultural lands.

4.4 Validation using NASS data

Table 4-3 classification accuracy compared to NASS data

FIPS	NAME	% wheat in total	Total NASS bytotal area	Location	Nass Irr %	Nass Nonirr %	Class Irr%	Class_ Nonirr %	Abs_Diff
189	Hale	12.9	54.2	Ps	75.3	24.7	80.2	19.8	**4.9**
303	Lubbock	3.6	50.1	Ps	57.4	42.6	44.5	55.5	**12.8**
219	Hockley	1.8	48.7	Ps	50.1	49.9	41.8	58.2	**8.3**
369	Parmer	52.1	47.4	Ps	60.5	39.5	68.8	31.2	**8.4**
69	Castro	42.9	46.4	Ps	74.3	25.7	83.0	17.0	**8.7**
153	Floyd	29.2	44.6	Ps	46.3	53.7	65.5	34.5	**19.2**
107	Crosby	5.6	38.6	Ps	49.4	50.6	46.9	53.1	**2.5**
437	Swisher	46.8	37.0	Ps	66.8	33.2	77.5	22.5	**10.8**
279	Lamb	18.2	35.0	Ps	60.7	39.3	64.8	35.2	**4.1**
79	Cochran	7.5	33.0	Ps	52.2	47.8	42.8	57.2	**9.4**
117	Deaf Smith	60.2	26.3	Ps	45.6	54.4	67.4	32.6	***21.8***
17	Bailey	33.8	24.9	Ps	34.7	65.3	44.6	55.4	**10.0**
381	Randall	84.0	16.7	Ps	8.0	92.0	71.7	28.3	***63.8***
45	Briscoe	41.5	11.9	Ps	59.7	40.3	56.9	43.1	**2.8**
11	Armstrong	77.3	11.9	Ps	4.7	95.3	71.8	28.2	***67.1***
325	Medina	20.1	8.0	U	53.6	46.4	80.5	19.5	***26.9***
463	Uvalde	16.8	5.9	U	70.5	29.5	81.7	18.3	**11.2**
29	Bexar	12.1	2.4	U	31.3	68.7	83.2	16.8	***51.9***

The counties in which GCPs were collected are highlighted in gray. Counties with more than 30 percent of their total are in row crop production showed greater accuracy of 80 percent or better, Table 4-3. The accuracy levels fell with an over estimation of non-Irrigated area in major wheat growing counties, Bexar, Randall and Armstrong because of the lack of non-Irrigated wheat GCPs used in classification. To fix this issue and improve accuracy collecting of more wheat GCPs is needed before field collected data or partner contributed is available this can be accomplished by using high resolution DOQQs and the CDL in the lab environment.

4.4 Validation of Classification using Partner Contributed data

Validation of irrigated lands classification with masking using independently obtained ground truth data points, supplied by PGCD (Panhandle Groundwater Conservation District). Only a validation on the irrigated portion of the classification could be performed because the GTPs received from PGCD were all irrigated. The accuracy of irrigation area in the classification was 88.6 percent, Table 4-4.

Table 4-4: Analysis of Ground truth data from PGCD

	Classification	Within Mask	Percent
InCorrect	Not Irr	35	11.4%
Correct	Irr	271	**88.6%**

5 Discussion

The methodology is successful in refinement of MODIS –NDVI products, prossesing GCPs, handling spectral signatures, Classification of the Megafile and masking to the areas of investigation. The current limiting factor is the signature data set. 2010 and 2011 were extreme weather conditions, from the present GCPs collected we are able to distinguish major crop type spectral signatures and classify between irrigated and non-irrigated areas clearly in Uvalde and Plainview study areas. We believe our classification of irrigated lands over non-irrigated lands would improve for other parts of the state if we had GCPs collected during a year with normal weather conditions. Data from external sources like ground water district agencies or well information from TWDB could also improve future classifications. Apart from the spectral signature databank and the above mentioned external datasets, the integration of NEXRAD data as an input to the model would give the process the ability to make logical decisions about weather conditions. Beside weather use of NEXRAD precipitation may be useful in comparing to NDVI values in order to exclude non-irrigated pixels from irrigated pixels in regions like Wharton and Cameron, if developed this method would enhance classification. In addition to NEXRAD use of high resolution datasets could be explored to address issues of field size, irrigation practices and precipitation in coastal areas.

The agland mask at present is based solely on CDL 2010 dataset, Since, FSA data would provide row crop irrigation information at county level, we plan to re-examine the FSA dataset for specific use in county level masking at statewide level in Phase II. In Phase I only major crop types have been investigated and with the use of 250m pixel sized MODIS NDVI any cropping areas of. 120 acres or more can be classified. Crops such as Alfa-alfa, irrigated forage/hay, vineyards, orchards and vegetables planted less than 60 acres cannot be identified using MODIS_NDVI 250m resolution products alone. In order to investigate these crops high resolution NAIP imagery could be used.

There is no issue with the present methodology to keep from continuing on to Phase II automation and the Spatial Sciences Laboratory at Texas A&M University is eager to move forward. The above mentioned additional methods would be tested and implemented during the

Phase II automation process. The additional methods have the potential to improve the classification performance in generating a more accurate statewide classification of irrigated and non-irrigated lands. In the current methodologies the only distinction made in the final classification is irrigated and non-irrigated areas. If in future classifications delineation between crop type and irrigation practice is desired this can be achieved by incorporating improved inputs to the current methodology. In the long run it is important to have an independent scientifically defendable estimate of irrigated acreages reported on an annual basis for use in water management. The current procedure is able to provide a classified map of Texas within three months from the end of growing season .This would benefit state and local agencies to track water use based on irrigated agricultural acreages, which in turn would help in decision making and strategic planning to conserve water.

6 Recommendations

With the long term goal of implementing this project on a yearly basis, the need to continue to expand the current signature database of irrigated and non-irrigated agriculture values is apparent. Addition of good signatures from a new collection of ground control points for a growing season under normal weather conditions is needed. The ground control points used in this project to build signature databases to classify irrigated versus non-irrigated agricultural lands was collected during extreme weather conditions. 2010 data was considered to be wet in most areas surveyed along with a faulty collection method in Wharton County and 2011 was the driest year recorded in Texas, both years representing outliers.

Another issue discovered was difficulty in accurately classifying coastal areas because of significant spectral signatures overlap due to weather and collection error in 2010. Similar limitations have been overcome by researchers by using temporal information on crop planting seasons, maturity, and harvest in conjunction with spectral information (Thenkabail and others, 2005). Unfortunately, collection of higher resolution remotely-sensed data is fixed by a given satellite's orbit, return interval and can be cost prohibitive, and observations are not always captured during maturity or harvest of a crop (Ozdogan and others, 2010). Deriving irrigated areas for coastal region is a challenge and new methods or different sensors might need to be adopted for the coastal regions of Texas.

To address the first issue with the support of TWDB officials we plan to obtain information on well data and statewide ground water district information data to incorporate it into the model along with future collected GCPs to improve the spectral signature database to be used in spectral matching, generating decision trees and classification. The second issue of classifying coastal regions may be dealt with by using precipitation data in combination with peak NDVI signatures to identify and isolate the irrigated and non-irrigated crops.

If given an opportunity to collect GCPs during normal weather conditions, it would be helpful to expand the signature database of NDVI thresholds from the current collection of ground control points under different irrigation management practices and specifically weather conditions. This would help the collection of signatures in capturing the diversity of crops during different years. The expansion of the signature database would enhance the current methodology and accuracy.

With support with TWDB and state agencies like PHGD, data from all over the state would provide useful information about irrigated and non-irrigated crops in all regions. This collaboration would be beneficial in accuracy assessment analysis and building of a better model for use in water management.

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8.1 Appendix A

- **Selection of the study area in Texas**

In consultation with TWDB, the following counties have been selected for developing the proof-of-concept in the first phase of this project:

Ogallala: Dallam, Dawson, Hale, and Floyd
Winter Garden: Uvalde
Rio Grande: Cameron
Rice Country: Wharton

- **Ground truthing locations**

2010

As proposed, one set of ground truthing data will be conducted during the growing season of 2010 by driving in the study area with a hand-held GPS (Global Positioning System) to collect land use/land cover information for the selected classes. All dataset collected were formatted as GIS-ready version.

The following table summarizes the field trips held by the project team to collect the necessary ground truth data

County	Dates visited	# of Ground control points collected
Wharton	6/11/2010 and 6/23/2010	126
Cameron	7/7/2010 – 7/9/2010	344
TX Panhandle	7/13/2010 – 7/14/2010	150
Uvalde/Medina	7/20/2010 – 7/22/2010	161

The distribution of the GCP collected during these field trips is illustrated in figures 1-5.

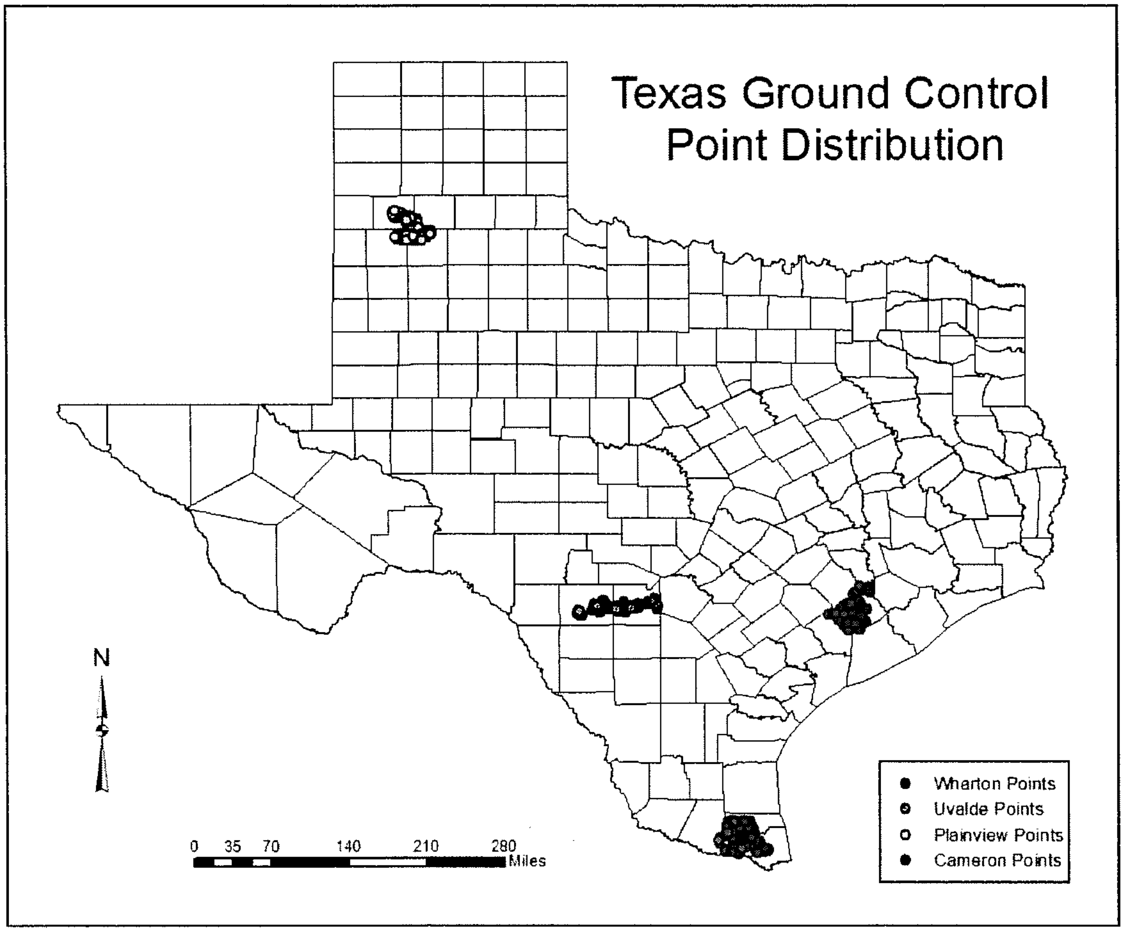

Figure 1: Distribution of GCPs in the pilot areas

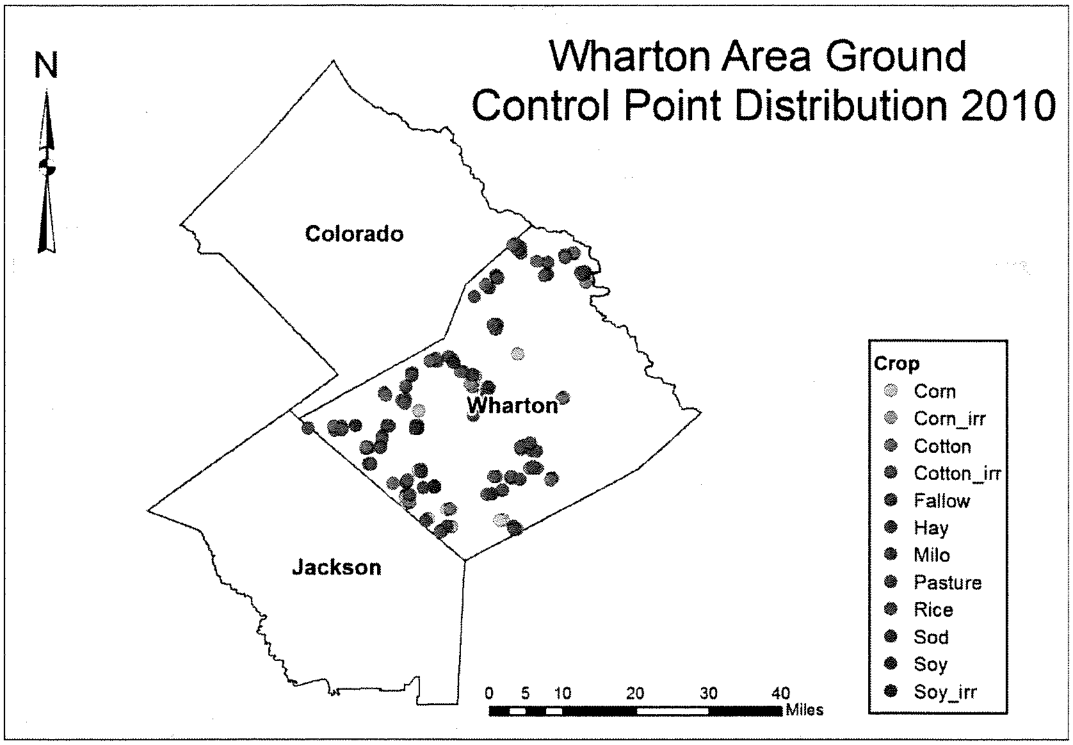

Figure 2: Distribution of GCPs in Wharton County ('irr' in the legend indicates irrigated)

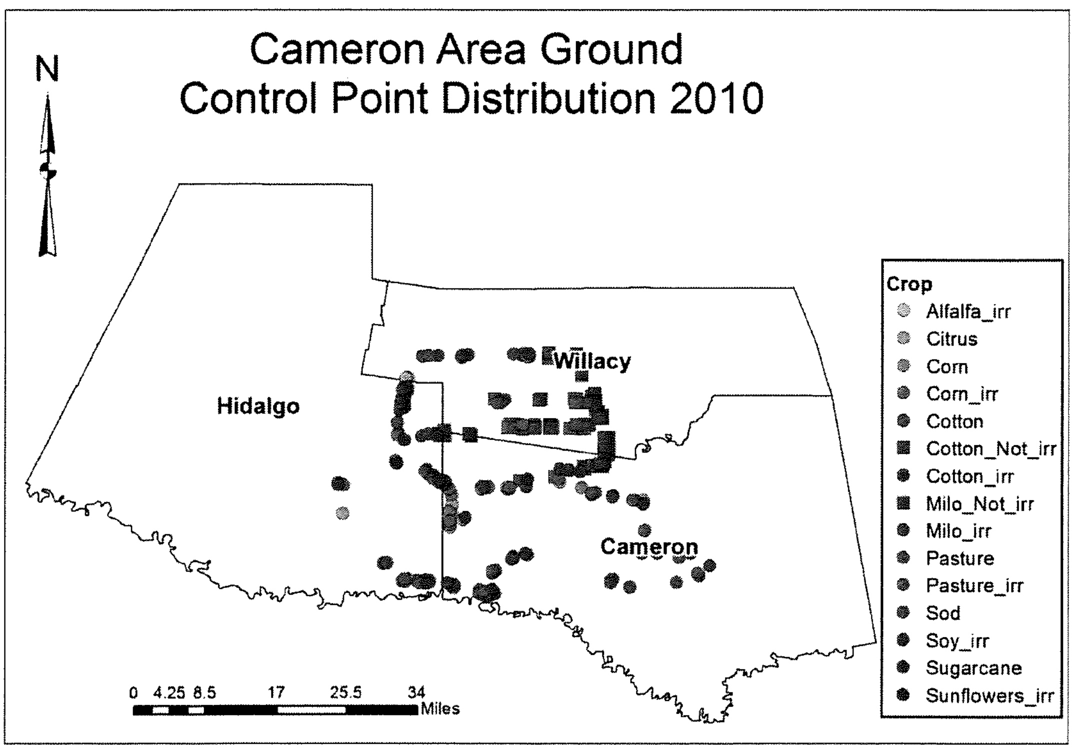

Figure 3: Distribution of GCPs in Cameron County

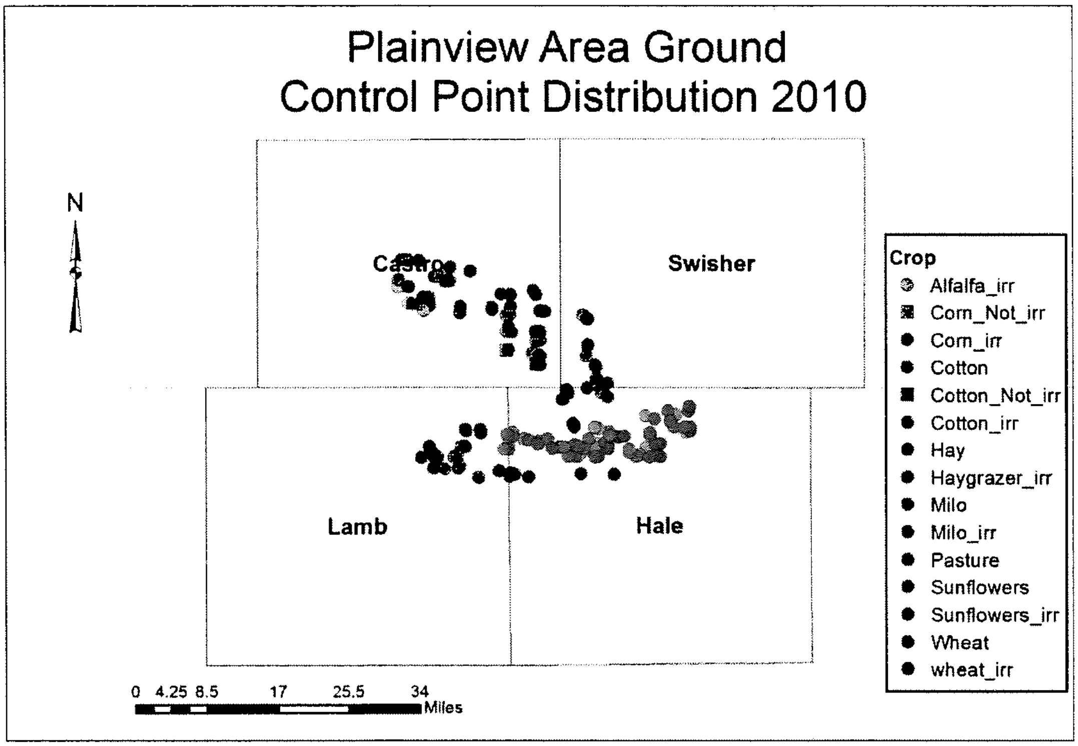

Figure 4: Distribution of GCPs in Texas Panhandle area

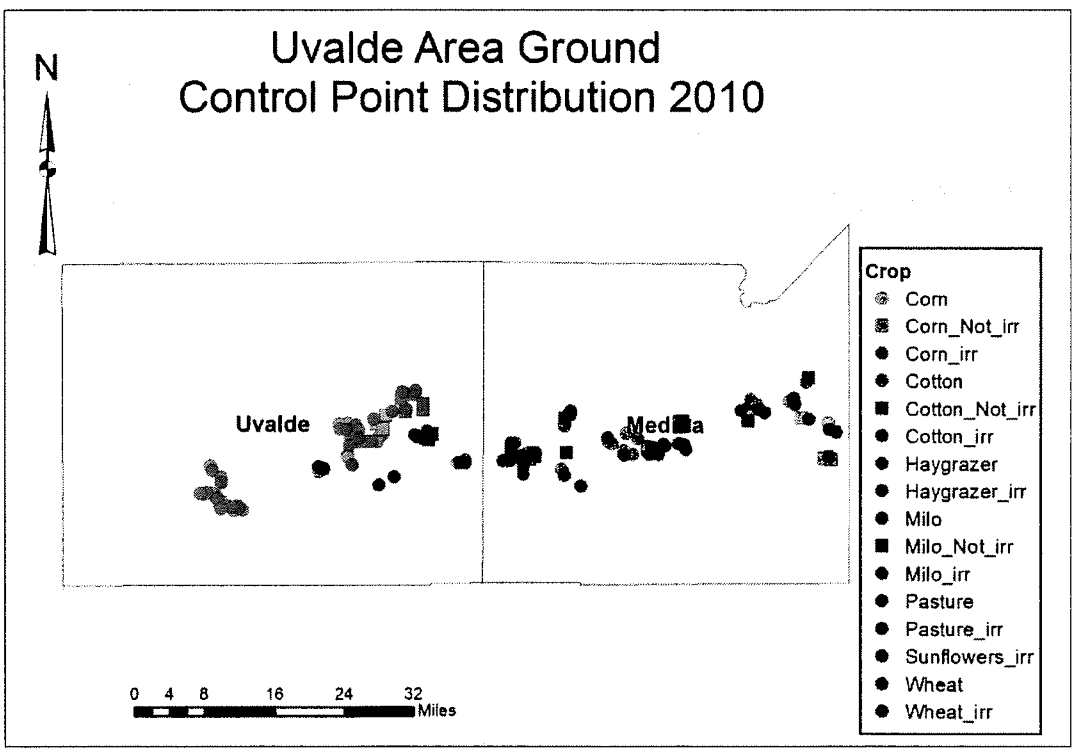

Figure 5: Distribution of GCPs in Uvalde/Medina (Winter Garden) Counties

2011

As proposed in the amended proposal of May 2011, a 2nd set of ground truthing data collection was conducted during the summer growing season of 2011 by driving in the study areas with a hand-held GPS (Global Positioning System) to collect land use/land cover information for the selected classes.

The following table summarizes the GCPs gathered this year compared to last year, grouped by area.

TWDB 2010/2011 Raw Field Data Points as of 7/14/2011												
Cameron			Jefferson		Plainview		Uvalde			Wharton		
	2010	2011		2011		2010		2010	2011		2010	2011
Alfalfa_irr	1	0	Alfalfa_irr	0	Alfalfa_irr	4	Alfalfa_irr	0	0	Alfalfa_irr	0	0
Citrus	25	7	Citrus	0	Citrus	0	Citrus	0	0	Citrus	0	0
Corn	2	0	Corn	0	Corn	0	Corn	0	0	Corn	17	0
Corn_irr	39	8	Corn_irr	0	Corn_irr	45	Corn_irr	49	82	Corn_irr	1	23
Corn_not_irr	0	1	Corn_not_irr	0	Corn_not_irr	1	Corn_not_irr	13	4	Corn_not_irr	0	14
Cotton	2	0	Cotton	0	Cotton	6	Cotton	2	0	Cotton	17	0
Cotton_irr	32	35	Cotton_irr	0	Cotton_irr	46	Cotton_irr	29	61	Cotton_irr	1	9
Cotton_not_irr	33	33	Cotton_not_irr	0	Cotton_not_irr	1	Cotton_not_irr	6	3	Cotton_not_irr	0	10
Fallow	0	1	Fallow	0	Fallow	0	Fallow	0	0	Fallow	8	0
Hay	0	0	Hay	0	Hay	1	Hay	1	0	Hay	2	2
Hay_irr	0	1	Hay_irr	0	Hay_irr	4	Hay_irr	2	0	Hay_irr	0	1
Milo	0	0	Milo	0	Milo	1	Milo	2	0	Milo	14	0
Milo_irr	61	31	Milo_irr	0	Milo_irr	8	Milo_irr	7	8	Milo_irr	0	0
Milo_not_irr	51	34	Milo_not_irr	0	Milo_not_irr	0	Milo_not_irr	17	6	Milo_not_irr	0	7
Pasture	10	9	Pasture	0	Pasture	11	Pasture	3	2	Pasture	16	11
Pasture_irr	24	1	Pasture_irr	0	Pasture_irr	0	Pasture_irr	2	3	Pasture_irr	0	1
Rice	0	0	Rice	17	Rice	0	Rice	0	0	Rice	41	14
Sod	3	0	Sod	0	Sod	0	Sod	0	0	Sod	2	0
Soy	0	0	Soy	0	Soy	0	Soy	0	0	Soy	6	1
Soy_irr	14	2	Soy_irr	0	Soy_irr	0	Soy_irr	0	0	Soy_irr	1	1
Sugarcan	45	19	Sugarcan	0	Sugarcan	0	Sugarcan	0	0	Sugarcan	0	0
Sunflowers	0	0	Sunflowers	0	Sunflowers	2	Sunflowers	0	0	Sunflowers	0	0
Sunflowers_irr	2	0	Sunflowers_irr	0	Sunflowers_irr	4	Sunflowers_irr	1	0	Sunflowers_irr	0	0
Unknown_Crop	0	0	Unknown_Crop	0	Unknown_Crop	0	Unknown_Crop	2	0	Unknown_Crop	0	0
Vegetable	0	3	Vegetable	0	Vegetable	0	Vegetable	1	0	Vegetable	0	0
Wheat	0	0	Wheat	0	Wheat	4	Wheat	14	10	Wheat	0	1
Wheat_irr	0	0	Wheat_irr	0	Wheat_irr	12	Wheat_irr	9	3	Wheat_irr	0	0
Total	344	185	Total	17	Total	150	Total	160	182	Total	126	95
Yearly Totals											780	479

Distribution of the GCPs collected during the 2011 field work is illustrated in figures 6-10.

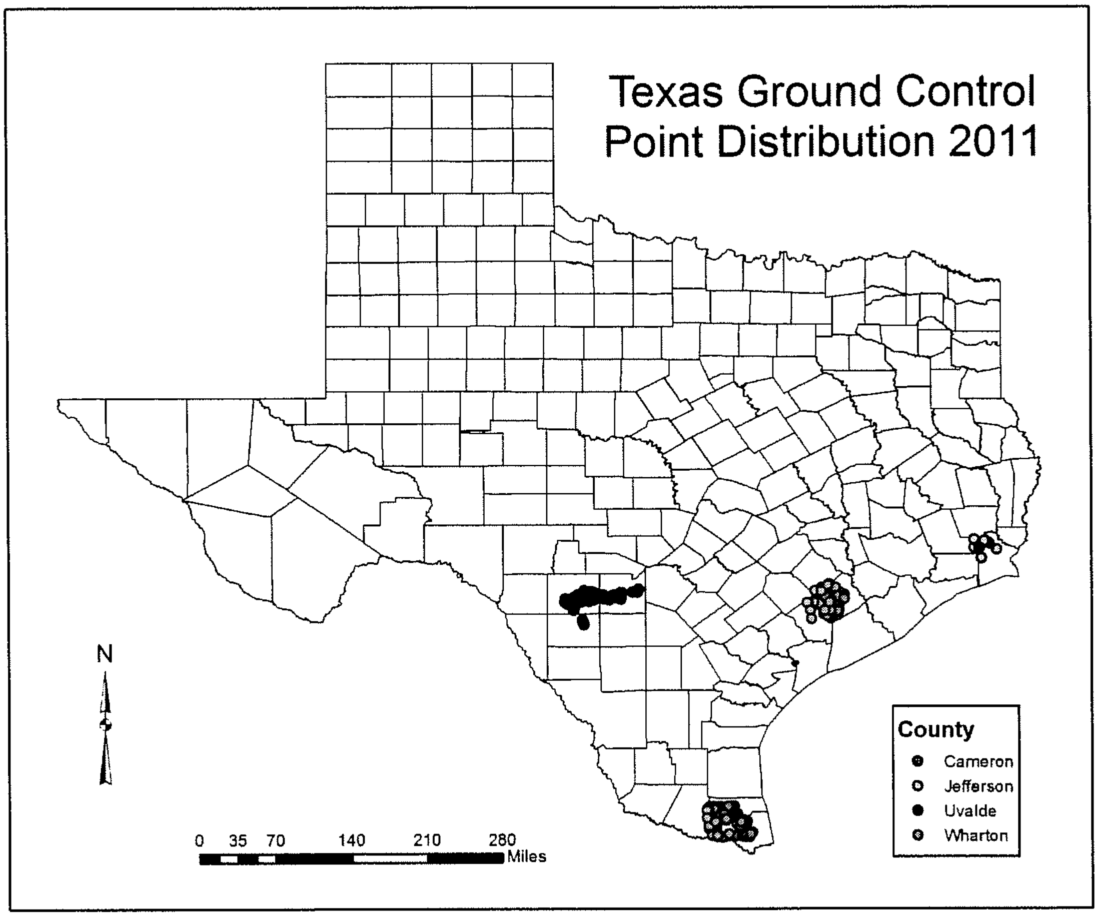

Figure 6: Distribution of GCPs

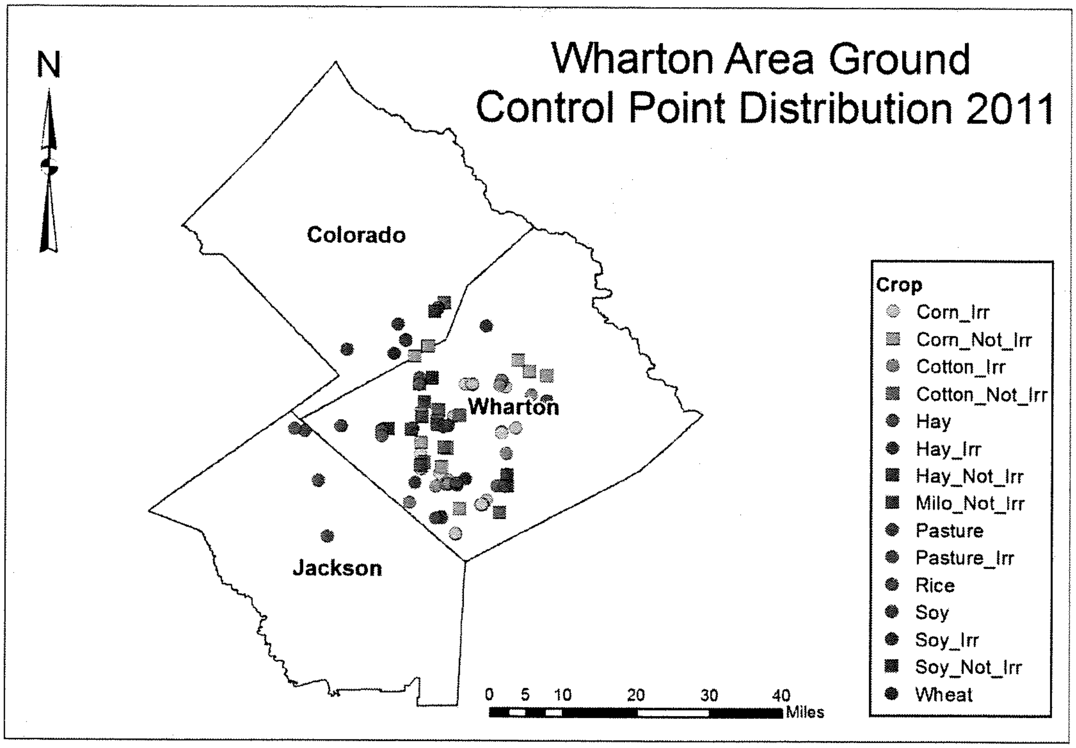

Figure 7: Distribution of GCPs in Wharton area

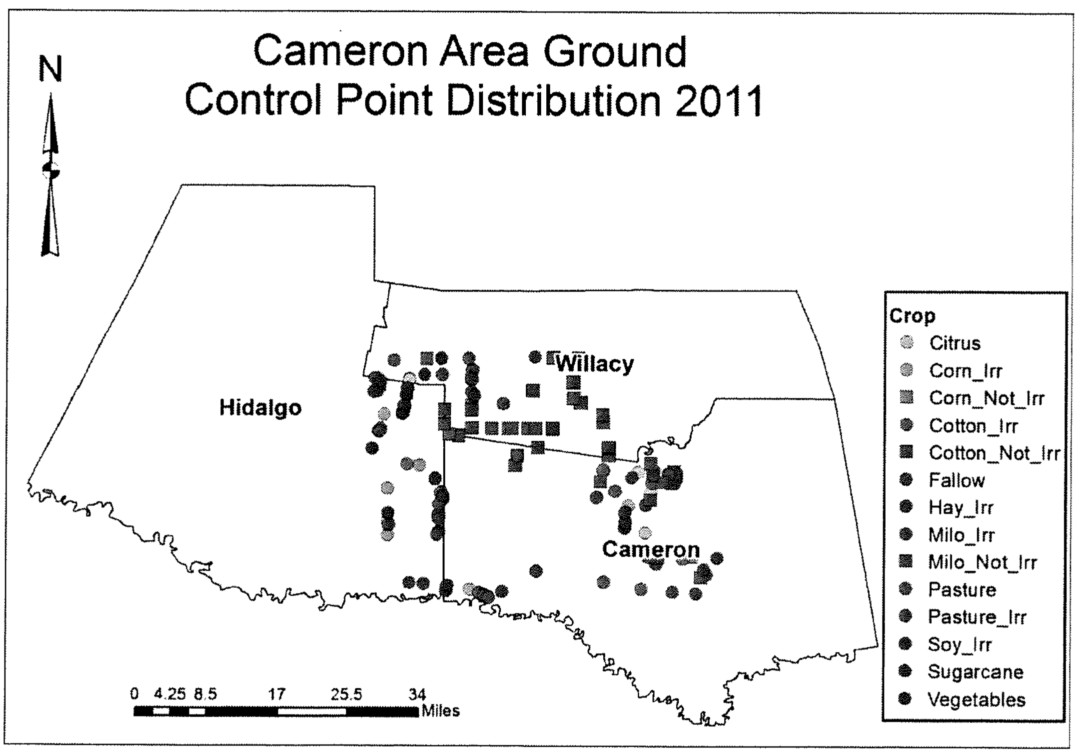

Figure 8: Distribution of GCPs in Cameron area

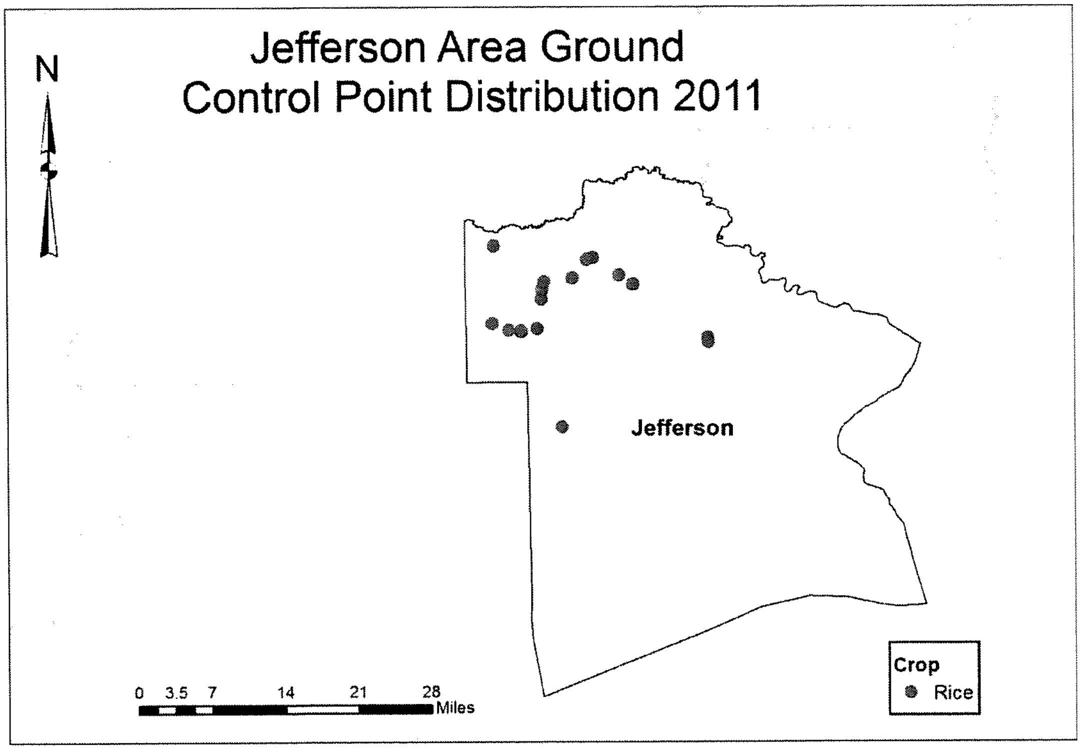

Figure 9: Distribution of GCPs in Jefferson County

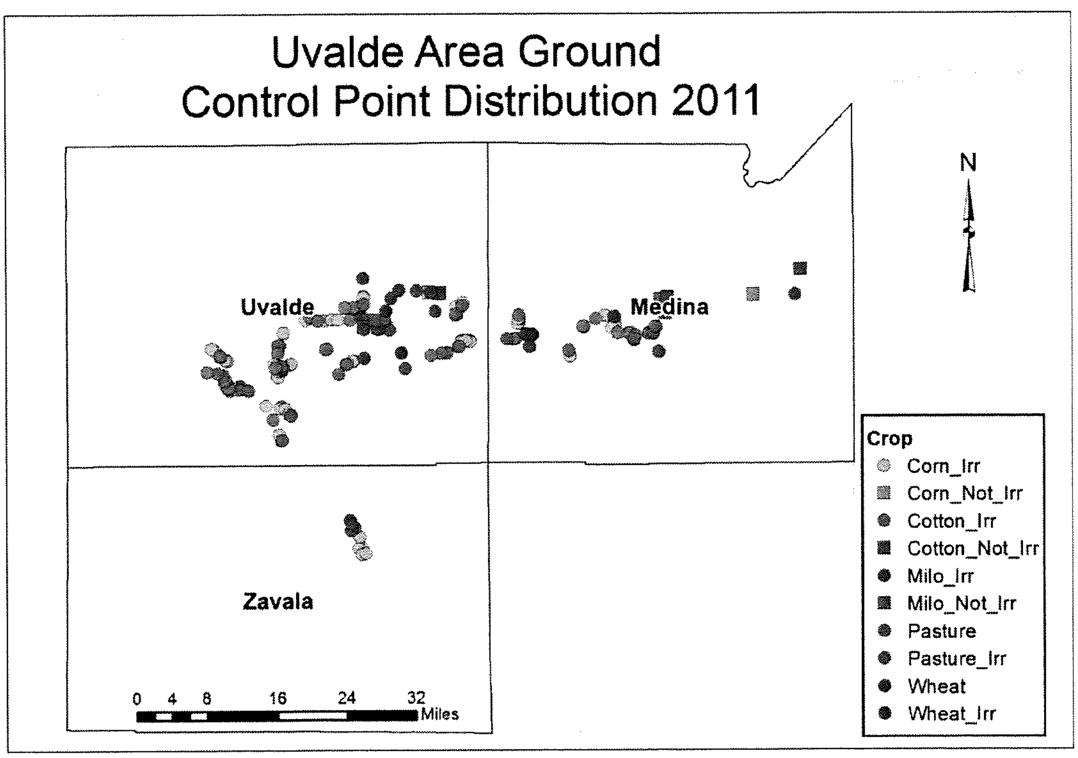

Figure 10: Distribution of GCPs in Uvalde area

- ## Moving Points

The collected GCPs that were not exactly located in the center of the fields were manually moved to the center of the fields using CDL and 0.5 meter DOQQs as references. This process was conducted to maximize the use of collected points and to avoid those points representing other surrounding landuse within 250 meter MODIS pixel.

- ## GCP clean up and classification

The classification of GCPs is currently conducted to rank all collected points by certainty although all collected points are valuable. Points collected at larger fields (e.g. larger than 250 meter radius) are ranked as primary points and will be used for analyses without uncertainty.

The collected 2010 ground control points from the Plainview area were again manually moved to the center of the corresponding fields using the New 2010 CDL and 1 meter NAIP images. This process was conducted a second time in order to use newer reference datasets that were not available the first time.

8.2 Appendix B

Software's used for the Project

Software	Source	Task
MODIS re-projection tool (MRT)	https://lpdaac.usgs.gov/tools/modis_reprojection_tool/	Projecting MODIS data
Time-series generator (TiSeG)	Rene Colditz (rene.colditz@conabio.gob.mx)	Removal of noise from MODIS data
ERDAS IMAGINE	http://geospatial.intergraph.com/Company/AboutUs.aspx	Mosaicking, signature extraction, classification
ENVI	http://www.exelisvis.com/ProductsServices/ENVI.aspx	Signature extraction
ArcMap	http://www.esri.com/	Data processing, refining GCPs and final classification output.
Microsoft office	http://office.microsoft.com/en-us/products/?CTT=97	Data processing, statistical analysis and report generation

8.3 Appendix C

"0" indicating disagreement with CDL classes and "1" indicating agreement with CDL classes
Cam- Cameron
Plan- Plainview
Uval- Uvlade
Whar- Wharton

Area	Field collected GCPs	Area_ID	GCP_to_crop	CDL_ID	CDL_name	CDL_to_crop	Correct
Cam	Milo_irr	139	Sorghum	1	Corn	Corn	0
Cam	Milo_irr	140	Sorghum	1	Corn	Corn	0
Cam	Cotton_irr	75	Cotton	2	Cotton	Cotton	1
Cam	Cotton_irr	88	Cotton	2	Cotton	Cotton	1
Cam	Cotton_irr	74	Cotton	2	Cotton	Cotton	1
Cam	Cotton_irr	76	Cotton	2	Cotton	Cotton	1
Cam	Cotton_Not_irr	125	Cotton	2	Cotton	Cotton	1
Cam	Cotton_Not_irr	122	Cotton	2	Cotton	Cotton	1
Cam	Cotton_Not_irr	120	Cotton	2	Cotton	Cotton	1
Cam	Cotton_Not_irr	101	Cotton	2	Cotton	Cotton	1
Cam	Cotton_Not_irr	104	Cotton	2	Cotton	Cotton	1
Cam	Cotton_Not_irr	115	Cotton	2	Cotton	Cotton	1
Cam	Cotton_Not_irr	107	Cotton	2	Cotton	Cotton	1
Cam	Cotton_Not_irr	110	Cotton	2	Cotton	Cotton	1
Cam	Cotton_Not_irr	114	Cotton	2	Cotton	Cotton	1
Cam	Cotton_Not_irr	116	Cotton	2	Cotton	Cotton	1
Cam	Cotton_Not_irr	128	Cotton	2	Cotton	Cotton	1
Cam	Cotton_Not_irr	119	Cotton	2	Cotton	Cotton	1
Cam	Milo_Not_irr	225	Sorghum	2	Cotton	Cotton	0
Cam	Milo_Not_irr	232	Sorghum	2	Cotton	Cotton	0
Cam	Milo_Not_irr	217	Sorghum	2	Cotton	Cotton	0
Cam	Milo_Not_irr	227	Sorghum	2	Cotton	Cotton	0
Cam	Milo_Not_irr	235	Sorghum	2	Cotton	Cotton	0
Cam	Soy_irr	286	Soy	2	Cotton	Cotton	0
Cam	Cotton_irr	77	Cotton	2	Cotton	Cotton	1
Cam	Cotton_irr	86	Cotton	2	Cotton	Cotton	1
Cam	Cotton_irr	87	Cotton	2	Cotton	Cotton	1
Cam	Cotton_Not_irr	124	Cotton	2	Cotton	Cotton	1
Cam	Cotton_Not_irr	130	Cotton	2	Cotton	Cotton	1
Cam	Cotton_Not_irr	126	Cotton	2	Cotton	Cotton	1
Cam	Cotton_Not_irr	108	Cotton	2	Cotton	Cotton	1

Cam	Cotton_Not_irr	105	Cotton	2	Cotton	Cotton	1
Cam	Cotton_Not_irr	118	Cotton	2	Cotton	Cotton	1
Cam	Cotton_Not_irr	117	Cotton	2	Cotton	Cotton	1
Cam	Cotton_Not_irr	123	Cotton	2	Cotton	Cotton	1
Cam	Cotton_Not_irr	127	Cotton	2	Cotton	Cotton	1
Cam	Cotton_Not_irr	112	Cotton	2	Cotton	Cotton	1
Cam	Milo_Not_irr	206	Sorghum	2	Cotton	Cotton	0
Cam	Milo_irr	149	Sorghum	171	Grassland Herbaceous	Pasture/Hay	0
Cam	Pasture_irr	270	Pasture/Hay	171	Grassland Herbaceous	Pasture/Hay	1
Cam	Pasture_irr	264	Pasture/Hay	181	Pasture/Hay	Pasture/Hay	0
Cam	Sugarcan	311	Sugarcan	181	Pasture/Hay	Pasture/Hay	0
Cam	Sugarcan	313	Sugarcan	181	Pasture/Hay	Pasture/Hay	0
Cam	Citrus	4	Citrus	4	Sorghum	Sorghum	0
Cam	Corn_irr	30	Corn	4	Sorghum	Sorghum	0
Cam	Corn_irr	58	Corn	4	Sorghum	Sorghum	0
Cam	Cotton_irr	69	Cotton	4	Sorghum	Sorghum	0
Cam	Cotton_Not_irr	111	Cotton	4	Sorghum	Sorghum	0
Cam	Milo_irr	178	Sorghum	4	Sorghum	Sorghum	1
Cam	Milo_irr	177	Sorghum	4	Sorghum	Sorghum	1
Cam	Milo_irr	152	Sorghum	4	Sorghum	Sorghum	1
Cam	Milo_Not_irr	236	Sorghum	4	Sorghum	Sorghum	1
Cam	Milo_Not_irr	229	Sorghum	4	Sorghum	Sorghum	1
Cam	Milo_Not_irr	238	Sorghum	4	Sorghum	Sorghum	1
Cam	Milo_Not_irr	239	Sorghum	4	Sorghum	Sorghum	1
Cam	Milo_Not_irr	228	Sorghum	4	Sorghum	Sorghum	1
Cam	Milo_Not_irr	202	Sorghum	4	Sorghum	Sorghum	1
Cam	Milo_Not_irr	233	Sorghum	4	Sorghum	Sorghum	1
Cam	Milo_Not_irr	237	Sorghum	4	Sorghum	Sorghum	1
Cam	Milo_Not_irr	223	Sorghum	4	Sorghum	Sorghum	1
Cam	Milo_Not_irr	226	Sorghum	4	Sorghum	Sorghum	1
Cam	Milo_Not_irr	216	Sorghum	4	Sorghum	Sorghum	1
Cam	Milo_Not_irr	212	Sorghum	4	Sorghum	Sorghum	1
Cam	Milo_Not_irr	215	Sorghum	4	Sorghum	Sorghum	1
Cam	Pasture_irr	262	Pasture/Hay	4	Sorghum	Sorghum	0
Cam	Soy_irr	288	Soy	4	Sorghum	Sorghum	0
Cam	Milo_Not_irr	234	Sorghum	4	Sorghum	Sorghum	1
Cam	Milo_Not_irr	214	Sorghum	4	Sorghum	Sorghum	1
Cam	Milo_Not_irr	205	Sorghum	4	Sorghum	Sorghum	1
Cam	Milo_Not_irr	207	Sorghum	4	Sorghum	Sorghum	1
Cam	Milo_Not_irr	204	Sorghum	4	Sorghum	Sorghum	1
Cam	Milo_Not_irr	194	Sorghum	4	Sorghum	Sorghum	1
Cam	Milo_Not_irr	193	Sorghum	4	Sorghum	Sorghum	1

Cam	Milo_Not_irr	230	Sorghum	4	Sorghum	Sorghum	1
Cam	Milo_Not_irr	211	Sorghum	4	Sorghum	Sorghum	1
Cam	Milo_Not_irr	198	Sorghum	152	Shrubland	Undefined	0

Area	**Field collected GCPs**	**Area_ID**	**GCP_to_crop**	**CDL_ID**	**CDL_name**	**CDL_to_crop**	**Correct**
Plan	Alfalfa_irr	3	Alfalfa	36	Alfalfa	Alfalfa	1
Plan	Corn_irr	7	Corn	1	Corn	Corn	1
Plan	Corn_irr	17	Corn	1	Corn	Corn	1
Plan	Corn_irr	13	Corn	1	Corn	Corn	1
Plan	Corn_irr	11	Corn	1	Corn	Corn	1
Plan	Corn_irr	8	Corn	1	Corn	Corn	1
Plan	Corn_irr	14	Corn	1	Corn	Corn	1
Plan	Corn_irr	39	Corn	1	Corn	Corn	1
Plan	Corn_irr	12	Corn	1	Corn	Corn	1
Plan	Corn_irr	42	Corn	1	Corn	Corn	1
Plan	Corn_irr	25	Corn	1	Corn	Corn	1
Plan	Corn_irr	24	Corn	1	Corn	Corn	1
Plan	Corn_irr	20	Corn	1	Corn	Corn	1
Plan	Corn_irr	19	Corn	1	Corn	Corn	1
Plan	Corn_irr	41	Corn	1	Corn	Corn	1
Plan	Corn_irr	49	Corn	1	Corn	Corn	1
Plan	Corn_irr	32	Corn	1	Corn	Corn	1
Plan	Corn_irr	30	Corn	1	Corn	Corn	1
Plan	Corn_irr	18	Corn	1	Corn	Corn	1
Plan	Milo_irr	110	Sorghum	1	Corn	Corn	0
Plan	Corn_irr	10	Corn	2	Cotton	Cotton	0
Plan	Cotton	55	Cotton	2	Cotton	Cotton	1
Plan	Cotton	52	Cotton	2	Cotton	Cotton	1
Plan	Cotton_irr	85	Cotton	2	Cotton	Cotton	1
Plan	Cotton_irr	58	Cotton	2	Cotton	Cotton	1
Plan	Cotton_irr	88	Cotton	2	Cotton	Cotton	1
Plan	Cotton_irr	91	Cotton	2	Cotton	Cotton	1
Plan	Cotton_irr	89	Cotton	2	Cotton	Cotton	1
Plan	Cotton_irr	84	Cotton	2	Cotton	Cotton	1
Plan	Cotton_irr	77	Cotton	2	Cotton	Cotton	1
Plan	Cotton_irr	102	Cotton	2	Cotton	Cotton	1
Plan	Cotton_irr	82	Cotton	2	Cotton	Cotton	1
Plan	Cotton_irr	80	Cotton	2	Cotton	Cotton	1
Plan	Cotton_irr	66	Cotton	2	Cotton	Cotton	1
Plan	Cotton_irr	62	Cotton	2	Cotton	Cotton	1
Plan	Cotton_irr	79	Cotton	2	Cotton	Cotton	1

Plan	Haygrazer_irr	106	Pasture/Hay	2	Cotton	Cotton	0
Plan	Milo_irr	111	Sorghum	2	Cotton	Cotton	0
Plan	Milo_irr	113	Sorghum	2	Cotton	Cotton	0
Plan	Cotton	56	Cotton	2	Cotton	Cotton	1
Plan	Cotton_irr	57	Cotton	2	Cotton	Cotton	1
Plan	Cotton_irr	101	Cotton	2	Cotton	Cotton	1
Plan	Cotton_irr	95	Cotton	2	Cotton	Cotton	1
Plan	Cotton_irr	94	Cotton	2	Cotton	Cotton	1
Plan	Cotton_irr	92	Cotton	2	Cotton	Cotton	1
Plan	Cotton_irr	86	Cotton	2	Cotton	Cotton	1
Plan	Cotton_irr	81	Cotton	2	Cotton	Cotton	1
Plan	Cotton_irr	59	Cotton	2	Cotton	Cotton	1
Plan	Cotton_irr	87	Cotton	2	Cotton	Cotton	1
Plan	Cotton_irr	73	Cotton	2	Cotton	Cotton	1
Plan	Cotton_irr	67	Cotton	2	Cotton	Cotton	1
Plan	Cotton_irr	76	Cotton	2	Cotton	Cotton	1
Plan	Cotton_irr	72	Cotton	2	Cotton	Cotton	1
Plan	Cotton_irr	71	Cotton	2	Cotton	Cotton	1
Plan	Cotton_irr	70	Cotton	2	Cotton	Cotton	1
Plan	Cotton_irr	60	Cotton	2	Cotton	Cotton	1
Plan	Cotton_irr	68	Cotton	2	Cotton	Cotton	1
Plan	Cotton_irr	63	Cotton	2	Cotton	Cotton	1
Plan	Cotton_irr	65	Cotton	2	Cotton	Cotton	1
Plan	Haygrazer_irr	108	Pasture/Hay	2	Cotton	Cotton	0
Plan	Milo_irr	112	Sorghum	2	Cotton	Cotton	0
Plan	Milo_irr	115	Sorghum	2	Cotton	Cotton	0
Plan	Pasture	127	Pasture/Hay	171	Grassland Herbaceous	Pasture/Hay	1
Plan	Pasture	124	Pasture/Hay	171	Grassland Herbaceous	Pasture/Hay	1
Plan	Pasture	128	Pasture/Hay	171	Grassland Herbaceous	Pasture/Hay	1
Plan	Alfalfa_irr	2	Alfalfa	171	Grassland Herbaceous	Pasture/Hay	0
Plan	Corn_irr	21	Corn	171	Grassland Herbaceous	Pasture/Hay	0
Plan	Hay	104	Pasture/Hay	171	Grassland Herbaceous	Pasture/Hay	1
Plan	Pasture	120	Pasture/Hay	171	Grassland Herbaceous	Pasture/Hay	1
Plan	Pasture	119	Pasture/Hay	171	Grassland Herbaceous	Pasture/Hay	1
Plan	Pasture	118	Pasture/Hay	171	Grassland Herbaceous	Pasture/Hay	1
Plan	Pasture	121	Pasture/Hay	171	Grassland Herbaceous	Pasture/Hay	1
Plan	Alfalfa_irr	1	Alfalfa	205	Triticale	Undefined	0

Plan	Corn_irr	22	Corn	205	Triticale	Undefined	0
Plan	Wheat	135	Wheat	24	Winter Wheat	Wheat	1
Plan	wheat_irr	146	Wheat	24	Winter Wheat	Wheat	1
Plan	wheat_irr	140	Wheat	24	Winter Wheat	Wheat	1
Plan	Wheat	138	Wheat	24	Winter Wheat	Wheat	1
Plan	Wheat	137	Wheat	24	Winter Wheat	Wheat	1
Plan	wheat_irr	145	Wheat	24	Winter Wheat	Wheat	1
Plan	wheat_irr	144	Wheat	24	Winter Wheat	Wheat	1
Plan	wheat_irr	148	Wheat	24	Winter Wheat	Wheat	1
Plan	wheat_irr	142	Wheat	24	Winter Wheat	Wheat	1
Plan	wheat_irr	143	Wheat	24	Winter Wheat	Wheat	1
Plan	wheat_irr	141	Wheat	24	Winter Wheat	Wheat	1
Plan	wheat_irr	139	Wheat	24	Winter Wheat	Wheat	1

Area	Field collected GCPs	Area_ID	GCP_to_crop	CDL_ID	CDL_name	CDL_to_crop	Correct
Uval	Corn_irr	32	Corn	1	Corn	Corn	1
Uval	Corn_irr	34	Corn	1	Corn	Corn	1
Uval	Corn_irr	36	Corn	1	Corn	Corn	1
Uval	Corn_irr	37	Corn	1	Corn	Corn	1
Uval	Corn_irr	38	Corn	1	Corn	Corn	1
Uval	Corn_irr	40	Corn	1	Corn	Corn	1
Uval	Corn_irr	46	Corn	1	Corn	Corn	1
Uval	Corn_irr	48	Corn	1	Corn	Corn	1
Uval	Corn_irr	49	Corn	1	Corn	Corn	1
Uval	Corn_irr	29	Corn	1	Corn	Corn	1
Uval	Corn_irr	11	Corn	1	Corn	Corn	1
Uval	Corn_irr	9	Corn	1	Corn	Corn	1
Uval	Corn_irr	2	Corn	1	Corn	Corn	1
Uval	Corn_irr	5	Corn	1	Corn	Corn	1
Uval	Corn_irr	8	Corn	1	Corn	Corn	1
Uval	Corn_irr	30	Corn	1	Corn	Corn	1
Uval	Corn_irr	17	Corn	1	Corn	Corn	1
Uval	Corn_irr	19	Corn	1	Corn	Corn	1
Uval	Corn_irr	20	Corn	1	Corn	Corn	1

Uval	Corn_irr	21	Corn	1	Corn	Corn	1
Uval	Corn_irr	23	Corn	1	Corn	Corn	1
Uval	Corn_irr	25	Corn	1	Corn	Corn	1
Uval	Corn_irr	26	Corn	1	Corn	Corn	1
Uval	Corn_irr	12	Corn	1	Corn	Corn	1
Uval	Corn_Not_irr	52	Corn	1	Corn	Corn	1
Uval	Corn_Not_irr	61	Corn	1	Corn	Corn	1
Uval	Corn_Not_irr	53	Corn	1	Corn	Corn	1
Uval	Corn_Not_irr	54	Corn	1	Corn	Corn	1
Uval	Corn_Not_irr	59	Corn	1	Corn	Corn	1
Uval	Corn_irr	33	Corn	1	Corn	Corn	1
Uval	Corn_irr	28	Corn	1	Corn	Corn	1
Uval	Corn_irr	47	Corn	1	Corn	Corn	1
Uval	Corn_irr	45	Corn	1	Corn	Corn	1
Uval	Corn_irr	24	Corn	1	Corn	Corn	1
Uval	Corn_Not_irr	51	Corn	1	Corn	Corn	1
Uval	Cotton_Not_irr	97	Cotton	1	Corn	Corn	0
Uval	Cotton_irr	79	Cotton	2	Cotton	Cotton	1
Uval	Cotton_irr	77	Cotton	2	Cotton	Cotton	1
Uval	Cotton_irr	73	Cotton	2	Cotton	Cotton	1
Uval	Cotton_irr	69	Cotton	2	Cotton	Cotton	1
Uval	Cotton_irr	80	Cotton	2	Cotton	Cotton	1
Uval	Cotton_irr	67	Cotton	2	Cotton	Cotton	1
Uval	Cotton_irr	89	Cotton	2	Cotton	Cotton	1
Uval	Cotton_irr	86	Cotton	2	Cotton	Cotton	1
Uval	Cotton_irr	70	Cotton	2	Cotton	Cotton	1
Uval	Cotton_irr	81	Cotton	2	Cotton	Cotton	1
Uval	Cotton_irr	68	Cotton	2	Cotton	Cotton	1
Uval	Cotton_irr	83	Cotton	2	Cotton	Cotton	1
Uval	Cotton_Not_irr	100	Cotton	2	Cotton	Cotton	1
Uval	Cotton_Not_irr	95	Cotton	2	Cotton	Cotton	1
Uval	Cotton_Not_irr	96	Cotton	2	Cotton	Cotton	1
Uval	Milo_Not_irr	126	Sorghum	2	Cotton	Cotton	0
Uval	Pasture_irr	133	Pasture/Hay	2	Cotton	Cotton	0
Uval	Cotton_irr	71	Cotton	2	Cotton	Cotton	1
Uval	Cotton_irr	76	Cotton	2	Cotton	Cotton	1
Uval	Cotton_irr	75	Cotton	2	Cotton	Cotton	1
Uval	Cotton_irr	90	Cotton	2	Cotton	Cotton	1
Uval	Cotton_irr	87	Cotton	2	Cotton	Cotton	1
Uval	Milo_irr	110	Sorghum	2	Cotton	Cotton	0
Uval	Vegetables	138	Vegetables	61	Fallow/Idle Cropland	Fallow	0
Uval	Wheat	146	Wheat	61	Fallow/Idle Cropland	Fallow	0

Uval	Milo_Not_irr	123	Sorghum	171	Grassland Herbaceous	Pasture/Hay	0
Uval	Wheat	143	Wheat	171	Grassland Herbaceous	Pasture/Hay	0
Uval	Cotton	64	Cotton	4	Sorghum	Sorghum	0
Uval	Cotton_Not_irr	99	Cotton	4	Sorghum	Sorghum	0
Uval	Milo	105	Sorghum	4	Sorghum	Sorghum	1
Uval	Milo	104	Sorghum	4	Sorghum	Sorghum	1
Uval	Milo_irr	112	Sorghum	4	Sorghum	Sorghum	1
Uval	Milo_Not_irr	124	Sorghum	4	Sorghum	Sorghum	1
Uval	Milo_Not_irr	125	Sorghum	4	Sorghum	Sorghum	1
Uval	Milo_Not_irr	117	Sorghum	4	Sorghum	Sorghum	1
Uval	Milo_Not_irr	127	Sorghum	4	Sorghum	Sorghum	1
Uval	Milo_Not_irr	114	Sorghum	4	Sorghum	Sorghum	1
Uval	Milo_Not_irr	113	Sorghum	4	Sorghum	Sorghum	1
Uval	Wheat_irr	155	Wheat	4	Sorghum	Sorghum	0
Uval	Milo_irr	109	Sorghum	4	Sorghum	Sorghum	1
Uval	Milo_irr	106	Sorghum	4	Sorghum	Sorghum	1
Uval	Milo_Not_irr	118	Sorghum	4	Sorghum	Sorghum	1
Uval	Milo_Not_irr	121	Sorghum	4	Sorghum	Sorghum	1
Uval	Milo_Not_irr	115	Sorghum	4	Sorghum	Sorghum	1
Uval	Milo_Not_irr	116	Sorghum	4	Sorghum	Sorghum	1
Uval	Cotton_irr	82	Cotton	142	Evergreen Forest	Undefined	0
Uval	Haygrazer_irr	103	Pasture/Hay	28	Oats	Undefined	0
Uval	Pasture	130	Pasture/Hay	152	Shrubland	Undefined	0
Uval	Pasture_irr	134	Pasture/Hay	28	Oats	Undefined	0
Uval	Unknown_Crop	137	Unknown_Crop	28	Oats	Undefined	0
Uval	Wheat	145	Wheat	152	Shrubland	Undefined	0
Uval	Wheat	142	Wheat	23	Spring Wheat	Wheat	1
Uval	Wheat	147	Wheat	24	Winter Wheat	Wheat	1
Uval	Wheat	152	Wheat	24	Winter Wheat	Wheat	1
Uval	Wheat	149	Wheat	24	Winter Wheat	Wheat	1
Uval	Wheat	148	Wheat	24	Winter Wheat	Wheat	1
Uval	Wheat	141	Wheat	24	Winter Wheat	Wheat	1
Uval	Wheat_irr	156	Wheat	23	Spring Wheat	Wheat	1
Uval	Wheat_irr	161	Wheat	23	Spring Wheat	Wheat	1
Uval	Wheat_irr	158	Wheat	24	Winter Wheat	Wheat	1
Uval	Corn_irr	7	Corn	24	Winter Wheat	Wheat	0
Uval	Wheat	144	Wheat	24	Winter Wheat	Wheat	1
Uval	Wheat_irr	153	Wheat	24	Winter Wheat	Wheat	1

Area	Field collected GCPs	Area_ID	GCP_to_crop	CDL_ID	CDL_name	CDL_to_crop	Correct
Whar	Corn	8	Corn	1	Corn	Corn	1
Whar	Corn	9	Corn	1	Corn	Corn	1
Whar	Corn	14	Corn	1	Corn	Corn	1
Whar	Corn	17	Corn	1	Corn	Corn	1
Whar	Corn	15	Corn	1	Corn	Corn	1
Whar	Corn	6	Corn	1	Corn	Corn	1
Whar	Corn	5	Corn	1	Corn	Corn	1
Whar	Corn	10	Corn	1	Corn	Corn	1
Whar	Corn	4	Corn	1	Corn	Corn	1
Whar	Milo	58	Sorghum	1	Corn	Corn	0
Whar	Corn	12	Corn	1	Corn	Corn	1
Whar	Corn	3	Corn	1	Corn	Corn	1
Whar	Corn	1	Corn	1	Corn	Corn	1
Whar	Corn	13	Corn	1	Corn	Corn	1
Whar	Corn	11	Corn	1	Corn	Corn	1
Whar	Corn_irr	18	Corn	1	Corn	Corn	1
Whar	Pasture	73	Pasture/Hay	1	Corn	Corn	0
Whar	Cotton	21	Cotton	2	Cotton	Cotton	1
Whar	Cotton	22	Cotton	2	Cotton	Cotton	1
Whar	Cotton	27	Cotton	2	Cotton	Cotton	1
Whar	Cotton	29	Cotton	2	Cotton	Cotton	1
Whar	Cotton	32	Cotton	2	Cotton	Cotton	1
Whar	Cotton	19	Cotton	2	Cotton	Cotton	1
Whar	Cotton	35	Cotton	2	Cotton	Cotton	1
Whar	Soy_irr	126	Soy	2	Cotton	Cotton	0
Whar	Cotton	30	Cotton	2	Cotton	Cotton	1
Whar	Cotton	23	Cotton	2	Cotton	Cotton	1
Whar	Cotton	24	Cotton	2	Cotton	Cotton	1
Whar	Cotton	26	Cotton	2	Cotton	Cotton	1
Whar	Cotton	20	Cotton	2	Cotton	Cotton	1
Whar	Cotton	31	Cotton	2	Cotton	Cotton	1
Whar	Cotton	28	Cotton	2	Cotton	Cotton	1
Whar	Cotton_irr	36	Cotton	61	Fallow/Idle Cropland	Fallow	0
Whar	Fallow	44	Fallow	61	Fallow/Idle Cropland	Fallow	1
Whar	Fallow	37	Fallow	61	Fallow/Idle Cropland	Fallow	1
Whar	Fallow	38	Fallow	61	Fallow/Idle Cropland	Fallow	1
Whar	Fallow	41	Fallow	61	Fallow/Idle Cropland	Fallow	1
Whar	Fallow	40	Fallow	61	Fallow/Idle Cropland	Fallow	1

Whar	Hay	46	Pasture/Hay	61	Fallow/Idle Cropland	Fallow	0
Whar	Pasture	64	Pasture/Hay	61	Fallow/Idle Cropland	Fallow	0
Whar	Pasture	68	Pasture/Hay	61	Fallow/Idle Cropland	Fallow	0
Whar	Pasture	66	Pasture/Hay	61	Fallow/Idle Cropland	Fallow	0
Whar	Pasture	71	Pasture/Hay	61	Fallow/Idle Cropland	Fallow	0
Whar	Pasture	62	Pasture/Hay	61	Fallow/Idle Cropland	Fallow	0
Whar	Pasture	70	Pasture/Hay	61	Fallow/Idle Cropland	Fallow	0
Whar	Pasture	67	Pasture/Hay	61	Fallow/Idle Cropland	Fallow	0
Whar	Pasture	63	Pasture/Hay	61	Fallow/Idle Cropland	Fallow	0
Whar	Pasture	69	Pasture/Hay	61	Fallow/Idle Cropland	Fallow	0
Whar	Pasture	76	Pasture/Hay	61	Fallow/Idle Cropland	Fallow	0
Whar	Pasture	72	Pasture/Hay	61	Fallow/Idle Cropland	Fallow	0
Whar	Fallow	42	Fallow	181	Pasture/Hay	Pasture/Hay	0
Whar	Fallow	39	Fallow	181	Pasture/Hay	Pasture/Hay	0
Whar	Pasture	75	Pasture/Hay	181	Pasture/Hay	Pasture/Hay	0
Whar	Pasture	61	Pasture/Hay	181	Pasture/Hay	Pasture/Hay	0
Whar	Pasture	74	Pasture/Hay	181	Pasture/Hay	Pasture/Hay	0
Whar	Pasture	65	Pasture/Hay	181	Pasture/Hay	Pasture/Hay	0
Whar	Rice	90	Rice	3	Rice	Rice	1
Whar	Rice	93	Rice	3	Rice	Rice	1
Whar	Rice	79	Rice	3	Rice	Rice	1
Whar	Rice	95	Rice	3	Rice	Rice	1
Whar	Rice	84	Rice	3	Rice	Rice	1
Whar	Rice	77	Rice	3	Rice	Rice	1
Whar	Rice	88	Rice	3	Rice	Rice	1
Whar	Rice	83	Rice	3	Rice	Rice	1
Whar	Rice	96	Rice	3	Rice	Rice	1
Whar	Rice	108	Rice	3	Rice	Rice	1
Whar	Rice	99	Rice	3	Rice	Rice	1
Whar	Rice	113	Rice	3	Rice	Rice	1
Whar	Rice	116	Rice	3	Rice	Rice	1
Whar	Rice	112	Rice	3	Rice	Rice	1
Whar	Rice	92	Rice	3	Rice	Rice	1
Whar	Rice	81	Rice	3	Rice	Rice	1
Whar	Rice	94	Rice	3	Rice	Rice	1
Whar	Rice	78	Rice	3	Rice	Rice	1

Whar	Rice	91	Rice	3	Rice	Rice	1
Whar	Rice	80	Rice	3	Rice	Rice	1
Whar	Rice	97	Rice	3	Rice	Rice	1
Whar	Rice	104	Rice	3	Rice	Rice	1
Whar	Rice	114	Rice	3	Rice	Rice	1
Whar	Rice	103	Rice	3	Rice	Rice	1
Whar	Rice	109	Rice	3	Rice	Rice	1
Whar	Rice	102	Rice	3	Rice	Rice	1
Whar	Rice	101	Rice	3	Rice	Rice	1
Whar	Rice	100	Rice	3	Rice	Rice	1
Whar	Rice	105	Rice	3	Rice	Rice	1
Whar	Rice	107	Rice	3	Rice	Rice	1
Whar	Rice	86	Rice	3	Rice	Rice	1
Whar	Rice	110	Rice	3	Rice	Rice	1
Whar	Rice	111	Rice	3	Rice	Rice	1
Whar	Rice	89	Rice	3	Rice	Rice	1
Whar	Milo	48	Sorghum	4	Sorghum	Sorghum	1
Whar	Milo	56	Sorghum	4	Sorghum	Sorghum	1
Whar	Sod	119	Pasture/Hay	4	Sorghum	Sorghum	0
Whar	Corn	7	Corn	4	Sorghum	Sorghum	0
Whar	Fallow	43	Fallow	4	Sorghum	Sorghum	0
Whar	Milo	52	Sorghum	4	Sorghum	Sorghum	1
Whar	Milo	51	Sorghum	4	Sorghum	Sorghum	1
Whar	Soy	124	Soy	5	Soybeans	Soy	1
Whar	Soy	121	Soy	5	Soybeans	Soy	1

Comments

General comments:

1. Please discuss in detail the specific tasks as outlined in the original Scope of Work and the 3 Objectives of Phase I including issues, adjustments, and status of completion.

   Objectives stated in the last paragraph page 4-5, and detailed explanation how we dealt with issues, adjustments are projected in our methods and result sections of the report as well as explained during the meeting on August 22 with TWDB.

2. Please expand upon the Background information (Task 1) provided in the draft report regarding previous research on the topic and development of your unique methods.

   Included in the background information, pages 3-5

3. Please be sure to address the status of the "timely report of irrigated acres and crop types at county level for four study areas validated with NASS/FSA data" as outlined in Objective #3, including a table with numbers determined by your methods and those numbers used for accuracy comparison.

   Added in the results section of the report, pages(22-23)

4. Please refer to "Exhibit D: Guidelines for Authors Submitting Contract Reports to the Texas Water Development Board" in the original contract document for information on formatting and editing the Phase I report.

   Referred to the "Exhibit D: Guidelines for Authors Submitting Contract Reports to the Texas Water Development Board" and made necessary edits

5. Please expand upon the methods used throughout Phase I in the main body of the report rather than only in Appendix A (combined Quarterly Reports). Consider moving much of Appendix A into the main body of the report.

   Moved appropriate current method information from previous "Appendix A (combined Quarterly Reports)" to the main body of the report, deleting previous, experimented tools and methods mentioned in combined quarterly reports.

6. Please consider including a "Master List" of abbreviated terms and phrases near the beginning of the report.

   Page iii

7. Please expand upon the results of the Pilot Study within the main text of the report. How did it affect the success of the overall study? Also, consider including the entire Pilot Study as a separate Appendix rather than within the combined quarterly reports.

   Pilot study was only an experiment to determine classification methods. It helped us to execute our current classification methods. This being a totally different classification and detailed explanation of this methodology was provided to TWDB during our quarterly report submission we feel it would not be necessary to include in the report as with the current methodology.

8. In the Scope of Work (2.3), it is stated "irrigation distinctions from various techniques and supplemental information derived from ground truthing, soil moisture, estimated evapotranspiration for the local region, crop phenology, rate of change of NDVI (or LA/), etc.". Please address each of these data and/or techniques in terms of their use in this study.

   Initially we planned to use above mentioned techniques and information (previous appendix A, combined quarterly reports), this was beginning of the project as we advanced during phase I we used ground truthing, NDVI, and crop phenology, pages 8-14.

9. Please include all TWDB comments as the last Appendix in the Phase I Final Report with an explanation for each comment and a page number(s) to where the changes may be found, if appropriate.

   Included

10. Along with a revised Phase I Report, please provide TWDB with all final products, source datasets, and significant interim datasets (classifications, decision trees, ground control points, signatures, metadata, etc.) that were developed through the work funded by this contract.

    Will be provided

<u>Specific comments by page number:</u>

11. pages v & vi: Please move much of the discussion in Appendix A into the main body of the report. After doing so, please update the Table of Contents, List of Figures, and List of Tables. (Also note, the Figure and Table numbers in Appendix A are repetitive I start over at "Figure 1" several times.)

    Fixed

12. page viii: Please add a "Definition of Key Terms" section at the beginning of the report.

Page iii

13. page 1, paragraph 3: Please explain further why an additional "normal year" would be needed. In early meetings, TWDB staff discussed with TAMU-SSL personnel the known challenges that the Eastern portion of the state would provide compared to the Western portion of the state in separating out irrigated and non-irrigated acreage. Please discuss your level of certainty that a "normal year" would actually improve confidence, and by how much, in the coastal regions and Eastern portion of the state. Please explain if this means Phase I is not yet adequately complete to continue with full confidence into the automation in Phase II.

Pages, 24-27

14. page 1, paragraph 4: While it is stated that confidence is high in these two regions for 2010, please assess your confidence in the 2011 values.

2011 values are assessed during phase II automation process

15. page 1, paragraph 5: Rather than mention the future possibilities that are contingent upon receiving additional funding to do something that is outside the current scope of work, please explain further the actual benefits gained from the work accomplished in Phase I and an assessment of your preparedness to go forward with Phase II.

Page 24-25

16. page 3, paragraph 1 (and elsewhere throughout): Please clearly define the terms "time-integrated", "time series", and "time-weighted" and check for consistent spelling.

Page iii

17. page 4: Please expand upon the accuracy and collection methods used by the appropriate agency to create the Crop Data Layer, the Farm Service Agency Planting Data, and the National Agricultural Statistics Service data set and how that accuracy figures into your study.

The CDL is a legacy program within NASS. Inputs into the CDL include satellite imagery from multiple sources, FSA Crop field data, NLCD, statistical information from NASS and the National Elevation Dataset. Accuracy on the CDL is assessed annually with the goal of 90 percent for major program crops.

FAS planting data and NASS reported totals are from non-compulsory programs they rely on participation and accurate reporting on surveys.

In order to use thes products with high confidence an accuracy of the cdl using the projects GCPs was performed, page 20, and when compare NASS data to the results percentages were used instead of acreages

18. page 4, paragraph 2 (also found on page 16): "The FSA data will be used for creating like areas of classification and for further refinement of the ag land mask." Please elaborate on this process and how it improves the accuracy of your methodology.

With the aggregation of planting data for many different crops, regions will be formed that share common planting traits. This will allow the creation of classifiers tailored to the specific regions raising accuracy by reducing the amount of area any one classifier applies to.

19. page 5, paragraph 1: "MOD13Ql ... has calculated vegetation indices based on a 16 day composite". Please elaborate on this product. How is it created and by whom? How might a composite image impact the recognition of spectral signatures during different crop growth stages?

Page 7

20. page 5, paragraph 3: "meter data can be used to reference the results". Please expand upon the methods used and explain why other classes were not validated.

Meter data was from PGCD which consisted of only irrigated crop information.

21. page 6, paragraph 1: In the Scope of Work (2.4) it is stated that "ground truthing data will be split into two sets", one for calibration and the other to validate the final classification. Please elaborate on this method and how it impacted accuracy. Please also address the following: why were all counties not visited in multiple years? Were points collected only from irrigated fields? Which crops were GPS located?

Accuracy of GCPs can be seen in results section

Why were all counties not visited in multiple years?

Due to extreme weather conditions

Were points collected only from irrigated fields? Which crops were GPS located?

Detailsof crop types and collections of GCPs can been seen in Appendix A

22. page 8, paragraph 1: Please describe the terms used here more completely (harmonic analysis, megafile, etc.).

Explained page 10-11

23. page 8, paragraph 2: Please distinguish between "ground truth locations" and "ground control points" including a thorough description of both the selection process and the collection process.

***Ground truth locations*- Are the GCPSs after moving and rating them to actual field sizes also called cleaned GCPs.**
***Ground control points*- Are the actual GCPs collected during field visits these are not corrected to field size**

24. page 9, paragraph 1: Please elaborate on the process of "shifting signatures", specifically in Figure 3. Is the shift to Plainview or to Uvalde; and why choose that shift rather than any of the other location choices? What crop types are represented in this figure?

Page 12

25. page 9, paragraph 2: Please expand upon the selection of supervised classification using decision trees as opposed to other techniques such as an object-oriented classification method.

Use of supervised classification was chosen over unsupervised for two reasons the ability to move a supervised classification to another area and once finalized the reduction of user inputs needed to run. Object-oriented classification was not used because of the low resolution of imagery designated for the project.

26. page 14, paragraph 1: Please elaborate on the "lengthy refinement process" of FSA data including justification for methods used and how these refinements positively or negatively impacted the accuracy of the study.

Explained with more examples Pages- 18-21

27. page 14, paragraph 3: Please more clearly define "DOSY" and how the use of this value benefits the study.

Explained with more examples Pages- 18-20

28. page 17, paragraphs 3&4: Please elaborate on the assessment of data accuracy, specifically:

- Was any ground truthing done to assess accuracy, or were the PGCD data used exclusively? **Yes results page-23**
- Was there any accuracy assessment in the other study areas? **Page-21**
- Were any collected ground truth points set aside for the accuracy assessment? **Yes**
- Was any attempt made to use Landsat data for validation in the study areas? **No**

29. page 18, paragraph 1: Please include a thorough discussion of your results through Phase I in addition to the Recommendations made herein.

Page-24-25

30. page 18, paragraph2: "Deriving irrigated areas for coastal region is a challenge and new methods or different sensors might need to be adopted for the coastal regions of Texas. For now exploration of the 2011 data is hoped to show an improvement, but as stated before more field work is needed especially for the coastal areas." Please elaborate on the current status of success and accuracy of methods used herein to identify irrigated lands near the coast.

Section 4 and 5

31. page 19: Please include in the list of references any and all literature reviewed for this study including the literature referenced in the Appendices.

Included

32. page 22, Task 2.1: Please elaborate on the selection of the study areas for Phase I including details on each area relevant to the study.

Appendix A

33. page 28, Task 2.3: The use of NEXRAD data is discussed in detail in the original grant application, however it is first mentioned in this report in the Appendix. Please elaborate on the use of ground based and remotely sensed weather data in accounting for increased NDVI values observed in this study.

Pages 24-26

34. page 29, Figure 1: Please explain the process and accuracy of identifying spectral signatures "averaged for several points within the county".

It was an initial idea not implemented in our current methodology

35. page 30, paragraph 1: "In order to achieve a reasonable accuracy it may be necessary to combine similar classes like com and sorghum or look simply at irrigated versus not irrigated crop types." Please expand upon this statement and discuss whether any adjustments to the methods positively impacted accuracy.

36. pages 35-44: It is difficult to distinguish so many different colored symbols in the figures.
Please consider altering the symbols to better reflect differences in crop type and irrigation status (such as a red circle for irrigated com and a red square for non-irrigated com). Also, please consider the possibility of showing these points atop the DOQQs for better visualization. Please also correct the Figure numbers throughout the report and appendix.

Corrected

37. page 44, paragraph 3: "The classification of GCPs is currently conducted to rank all collected points by certainty although all collected points are valuable. Points collected at larger fields (e.g. larger than 250 meter radius) are ranked as primary points and will be used for analyses without uncertainty." Please elaborate on this ranking process and how this "uncertainty" affects accuracy.

Explained the ranking process on field sizes was due to classifying our images using MODIS 250m products more details in section 3

38. page 58, paragraph 2: "Similar spectral signature banks for different crop types are planned to be developed for distinct ecoregions for the state". Please elaborate on the status of the identification of spectral signatures by crop type and region and on the accuracy of these signatures.

Pages 24-26

39. page 58, paragraph 3: "It will be important to understand all of the variables that affect NDVI values for specific crops. Annual rainfall in Texas ranges from less than 15 inches to greater than 54 inches from west to east. Variation in temperature from north to south and east to west should also be considered." Please elaborate on how the issues raised in this portion of the discussion have been addressed and have impacted the study.

40. page 58: Please include a brief discussion of future work, including:

a. What kind of training would you provide to TWDB staff as part of Phase II?
b. How would it be implemented?

a & b : The training of TWDB staff on the methodologies current at the end of Phase II and on operating and modification of the model built in phase II would be done in person in Austin, TX and /or College station, TX with additional support available by email and phone.

41. page 59: As this is the end of Phase I, please provide an explanation of your preparedness and readiness to begin an automated assessment at the statewide level including automatic data collection, processing, map creation, and maintenance.

We are prepared for the automated process, our data collection and processing using MODIS projection tool, time series generator are automated tools. Though, these tools are automated there is need for human interventions in decision making in creating maps and combining all these tools which need be automated in PhaseII. And page 25.

42. Page 59: Please update the descriptions of the "Other Activities" listed and include the full date when each activity was completed.

Other activites section excluded from the report

Addendum to Draft Interim Report Comments

TWDB Ag Grant Contract # 0903580957 with TAMU – Texas AgriLife Research,

Estimation of Irrigated Landuse Using Time-Integrated Remotely Sensed Data

Phase I completion project meeting follow-up comments

In addition to the Phase I draft report comments sent on August 07, 2012, please consider incorporating your responses to each of these additional comments made following the Review of Phase I presentation on August 22, 2012.

A1. Please be sure to include a full review of current literature in this report, as outlined in the Scope of Work, Task 1.

Full literature review along with references in PHASE I report section 2

A2. In the original grant application (Task 2.4) a target was set of "50 samples per class" regarding ground truthing as validation. Please elaborate on the process that ensured your points were both spatially and thematically representative. Please also address whether or not any field data were collected in 2012.

Initially, we planned on 50 samples per class, but due to practical reasons like weather conditions, field size and local seasonal patterns we were not able to collect 50 GCP points per class.

There was no field data collection during 2012 because we focused our efforts on the consolidation of methodologies into a coherent process for the creation of the Phase I report. With help of TWDB, collaborations from other statewide agencies information on irrigated and non-irrigated crop types would increase our crop type class GCPs.

A3. Regarding accuracy assessment, please consider including a table which thoroughly details accuracy by crop type including information on correct pixels, producer's accuracy, errors of omission, kappa coefficient, user's accuracy, errors of commission, conditional kappa, and overall accuracy.

Our accuracy assessment can be done only to "Irrigated"; "Non_irrigated" class types and does not distinguishable to crop specific types. Unfortunately at this point we are not able to give a crop type accuracy assessment with our classification but can provide you with GCPs and CDL crop specific accuracy assessment due to following reasons.

Our goal in phase I was to have our GCPs database built, consolidate our methods and temporally and spatially classify irrigated, non-irrigated land and our GCPs collected test accuracy. In phase II we can do a crop specific classification and accuracy assessment by crop type.

Regarding #41 in the original comments ["*page 59: As this is the end of Phase I, please provide an explanation of your preparedness and readiness to begin an automated assessment at the statewide level including automatic data collection, procession, map creation, and maintenance*"]:

- Please provide an estimate of your confidence in the methodology for areas other than the High Plains, which was stated as 80+ percent in the meeting. What is your confidence in automation of the methodology for Uvalde, Cameron, Wharton counties, and statewide?

  We are confident about High plains and Uvalde regions. Our major concern was Cameron and Wharton areas were we plan to change our inputs to our current methodology for the coastal areas and also include NEXRAD dataset to improve our classification (Page 24). With these changes in the inputs we are confident enough to say we are prepared for PHASE II automation process of statewide classification.

- Please also include a projected time line for proposed Phase II work.

  18 months from Phase II approval by TWDB.

A4. Please elaborate on the reliability of the methods developed herein in detecting smaller fields, multi-crop fields, fields near the coast, fields in east Texas, and crops such as alfalfa, irrigated forage / hay crops, and vineyards or orchards and how these issues might impact the efforts to apply this method to the entire state.

There is a tradeoff between classification based on major crops providing an up to date temporal and spatial classification using MODIS products or classification of minor crops like alfalfa, irrigated forage / hay crops, and vineyards or orchards, which can be detected using NAIP imagery or Landsat but have to lose temporal information and restrict ourselves to specific spatial locations. Classification of multi-crop fields, fields near the coast, fields in east Texas, and crops such as alfalfa, irrigated forage / hay crops, and vineyards or orchards can be achievable if needed by our funding agency, but would require more field data (may be information from statewide agencies or manual field collection), time cleaning the datasets and processing time especially for addition to the automation at the statewide level.

A5. Please elaborate on the usefulness of this technique as it relates to all irrigated agriculture in Texas, not just for those crops considered 'major'. How successful is this sensor at distinguishing signatures for these minor crops? Why were certain crops such as alfalfa masked out of the classification image?

By the end of Phase II automation process we are able to provide classified maps of irrigated agriculture within three months after the growing season on a continuous basis. With additional scientific vigor this can be fully implemented in providing high quality outputs for continuous monitoring of irrigated and non-irrigated lands. Sensor is effective in distinguishing crops types with field size larger than 120 acres anything less than that is a tradeoff between finer spatial information or based on temporal information. Alfa alfa was not excluded from our GCP database or mask; it was included in our irrigated, non-irrigated land classification. But there were very few Alfalfa GCP points collected, which we plan on improving collection during Phase II.

A6. Please elaborate on the justification for removal of portions of the U.S. Department of Agriculture – Farm Service Agency (FSA) data (e.g. less than 5 acres, etc.) and how the removal of these data might affect the overall accuracy of comparisons between FSA estimates and your own.

Thresholds for refining FSA date were set at levels well below what the resolution of the sensor (250m MODIS) we are using in the methods could detect.

A7. Please provide a table of the accuracy for each crop within the U.S. Department of Agriculture – National Agricultural Statistics Service' cropland data layer.

Table provided in Appendix C, this comparison is only based on crop type not the irrigation practice.

A8. Please include in your report information on how much time and cost would be associated with the automation portion of the project once the technology is transferred to the Texas Water Development Board. Please also detail specifically what Phase II would entail and document whether anything from the original contract would need to be amended.

Phase II automation process would be completed in 18 months and cost of around 150 K, at present original contract remains the same, may be a mutually agreeable task to enhance the project outcome can be added. A detailed document of tasks in phase II

would be mailed to TWDB in couple of weeks after submission of phase I final report to TWDB.

A9. Along with the Phase I Final Interim Report, according to the contract requirements, please deliver all of the following:

- a description of the research performed; **Section 2 in final report**
- the methodology and materials used; **Section 3 in final report**
- any diagrams or graphics used to explain the procedures related to the study; **Included in the final report**
- any data collected; **Will be sent to TWDB**
- an electronic copy of any computer programs, maps, or models along with an operations manual and any sample data set(s) developed under the terms of this contract; **Will be sent to TWDB**
- analysis of the research results; **Section 4 in final report**
- conclusions and recommendations; **Section 5 and 6 in final report**
- a list of references, a Table of Contents, List of Figures, List of Tables, an Executive Summary; and **final report**
- any other pertinent information.

A hard copy of the report along with datasets will be mailed to TWDB in in the week fallowing electronic submission or later if instructed to do so by TWDB.

A10. Please include a copy of these comments in the Final Interim (Phase I) Report with responses and/or reference to where responses may be found in the report, where applicable.

Corrections made and included