# USING HISTORICAL LANDSAT TM SATELLITE IMAGERY FOR ON-FARM MANAGEMENT DECISIONS IN HARD RED WINTER WHEAT

By

### CARLY NICOLE WASHMON

Bachelor of Science

Oklahoma State University

Stillwater, OK

1999

Submitted to the Faculty of the Graduate College of the Oklahoma State University in partial fulfillment of the requirements for the Degree of MASTER OF SCIENCE July 2005

## USING HISTORICAL LANDSAT TM SATELLITE

### IMAGERY FOR ON-FARM MANAGEMENT

## DECISIONS IN HARD RED

## WINTER WHEAT

Thesis Approved:

Dr. John B. Solie

Thesis Adviser Dr. Marvin Stone

Dr. William Raun

A. Gordon Emslie

Dean of the Graduate College

# PREFACE

This thesis is the culmination of many years of research and work looking for positive uses for Landsat TM satellite imagery in agricultural production. Winter wheat is the number one cash crop in Oklahoma, and therefore was the focus of this research.

I would like to thank my major advisor, Dr. John Solie, for his time, guidance and support given through my years at Oklahoma State University. He has been not only an advisor, but a friend, colleague and someone very dear to me. I would also like to thank my committee members, Dr. Marvin Stone and Dr. William Raun, for their assistance and support during this project. I would be remiss if I did not thank my family for all of their support through all of my years. I know my father is watching over me and smiling. I also would like to thank Greg for his faith in my abilities, his support, and his love.

I would like to acknowledge the organizations that contributed funding: The Oklahoma Wheat Commission, NASA, and USDA. Additionally, I would like to acknowledge the farmers that gave me not only time, but assistance and understanding to help me see the big picture when it comes to farming in Oklahoma. These farmers included J.C. Fath, Kenneth Failes, Jim Kent, Joe Peeper, Clarion Gies, Alan Weins, and John Linn. I would also like to express my gratitude to Roger Gribble of the Oklahoma State University Extension Service. His assistance made the contact with the farmers possible.

## TABLE OF CONTENTS

Chapt	ter	Page
I.	Within Field Variability in Wheat Grain Yields Over Nine Years In Okla	thoma
		1
II.	Creating Management Zones Using Landsat TM Imagery	14
III.	APPENDIX A. Carrier Farm	45
IV.	APPENDIX B. Cherokee Farm	55
V.	APPENDIX C. Hitchcock Farm	65
VI.	APPENDIX D. Red Rock Farm	73
VII.	APPENDIX E. Tonkawa West Farm	84

## LIST OF TABLES

Ta	Table		
1.	Statistics for estimated yield values using NDVI collected from LANDSAT		
	Images, 1991-1999, at six locations in Oklahoma	7	
2.	Dates of the Landsat Thematic Mapper scenes used in the study	21	

## LIST OF FIGURES

Figure	Page			
1. 1998 Landsat TM image for north central Oklahoma, taken April 23				
2. Mean yield plot for all fields.	8			
3. Error calculated by predicted yields with average years of historical data	8			
4. 1998 Landsat TM image for north central Oklahoma, taken April 23	21			
5. Satellite image for OSU Wheat Pasture Research Center before and after				
raster to vector conversion process	22			
6. Satellite image of OSU Wheat Pasture Research Center with				
paddock boundaries	24			
7. The correlation between the satellite image NDVI and the predicted yield	26			
8. Tonkawa West farm aerial imagery and average normalized yields				
over six year period	31			
9. Tonkawa west farm 1993 corrected yield	32			
10. Red Rock farm aerial imagery and normalized average yields	34			
11. Red Rock farm soil classification illustration	35			
12. Hitchcock farm average normalized yields over six years of data	36			
13. Hitchcock farm soil classification illustration	36			
14. Aerial image of Carrier farm's fields	37			
15. Carrier farm average normalized yields after 6 years of data	38			

Figure	Page
16. 1992 Carrier farm yield surface	38
17. Carrier farm illustration of hail damage line from 1999 storm	39
18. Example of satellite imagery of Carrier farm, acquisition date of	
April 23, 1998	46
19. Carrier farm predicted yield (bu/ac) surface. Effects of grazing can	
be seen in lower yield prediction areas	47
20. Carrier farm 992 predicted yield (bu/ac) surface. Disease affected	
the yield predictions in three of the fields	48
21. Carrier farm 993 predicted yield (bu/ac) surface. Standing water	
lowered yield potential in southern areas of the farm	49
22. Carrier farm 1994 predicted yield (bu/ac) surface	50
23. Carrier farm 1996 predicted yield (bu/ac) surface	51
24. Carrier farm 1998 predicted yield (bu/ac) surface. One field was not plan	ted 52
25. Carrier farm 1999 predicted yield (bu/ac) surface. Effects of hail damage	
can be seen in the northern fields	53
26. Carrier farm average normalized yield raster surface	54
27. Example of satellite imagery of Cherokee farm, acquisition date	
of April 28, 1998	56
28. Cherokee farm 1991 predicted yield (bu/ac) raster surface	57
29. Cherokee farm 1993 predicted yield (bu/ac) raster surface	58
30. Cherokee farm 1994 predicted yield (bu/ac) raster surface	59

Fig	ure	Page
31.	Cherokee farm 1996 predicted yield (bu/ac) raster surface	60
32.	Cherokee farm 1997 predicted yield (bu/ac) raster surface	61
33.	Cherokee farm 1998 predicted yield (bu/ac) raster surface	62
34.	Cherokee farm 1999 predicted yield (bu/ac) raster surface	63
35.	Cherokee farm average normalized yields divided into management zones	64
36.	Hitchcock farm 1992 predicted yield (bu/ac) raster surface	66
37.	Hitchcock farm 1993 predicted yield (bu/ac) raster surface	67
38.	Hitchcock farm 1994 predicted yield (bu/ac) raster surface	68
39.	Hitchcock farm 1996 predicted yield (bu/ac) raster surface	69
40.	Hitchcock farm 1998 predicted yield (bu/ac) raster surface	70
41.	Hitchcock farm 1999 predicted yield (bu/ac) raster surface	71
42.	Hitchcock farm average normalized yield, from six years of data,	
	divided into management zones.	72
43.	Example of Red Rock farm satellite imagery, acquired on April 28, 1998	74
44.	Red Rock farm 1991 predicted yield (bu/ac) raster surface	75
45.	Red Rock farm 1992 predicted yield (bu/ac) raster surface	76
46.	Red Rock farm 1993 predicted yield (bu/ac) raster surface	77
47.	Red Rock farm 1994 predicted yield (bu/ac) raster surface	78
48.	Red Rock farm 1996 predicted yield (bu/ac) raster surface	79
49.	Red Rock farm 1997 predicted yield (bu/ac) raster surface	80
50.	Red Rock farm 1998 predicted yield (bu/ac) raster surface	81
51.	Red Rock farm 1999 predicted yield (bu/ac) raster surface	82

Fig	ure	Page
52.	Red Rock farm average normalized yield surface, divided into	
	management zones	83
53.	Example of Tonkawa West farm satellite imagery, acquired on	
	April 28, 1998	85
54.	Tonkawa West farm 1991 predicted yield (bu/ac) raster surface	86
55.	Tonkawa West farm 1992 predicted yield (bu/ac) raster surface	87
56.	Tonkawa West farm 1993 predicted yield (bu/ac) raster surface	88
57.	Tonkawa West farm 1996 predicted yield (bu/ac) raster surface	89
58.	Tonkawa West farm 1997 predicted yield (bu/ac) raster surface	90
59.	Tonkawa West farm 1998 predicted yield (bu/ac) raster surface	91
60.	Tonkawa West farm 1999 predicted yield (bu/ac) raster surface	92
61.	Tonkawa West farm average normalized yield surface divided	
	into management zones	93

# LIST OF EQUATIONS

Equation	Page
<ol> <li>NDVI Calculation</li> <li>Exponential Yield Prediction Equation</li> </ol>	23

Z

CHAPTER I.

#### **INTRODUCTION**

In the past few years there has been an increasing demand for new technologies to assist farmers in making decisions for inputs and to manage variability within fields. Looking at historical data has been suggested to allow for increased accuracy in management decisions. Baier (1979) stated that correct decisions are dependent on timely and accurate information. Crop yield maps are designed to represent the relationship between the crops and their environment. When looking at historical yield to create one of these models, there are many causes for error that must be addressed.

Many different variables can be acquired and used to make input decisions. Larson (1986) compared crop yields between soil types and found that managing spatially variable fields based on the variability of soil type increased net returns. What information do we need to make an appropriate decision? Bakhsh, et al. (2000) used a statistical approach to characterize the spatio-temporal variability within a field. They found that overall, yield variability was not stable spatially or temporally. Their objective was not to develop a yield model, but they hypothesized that one major cause of yield variation was interaction among soil water retention capacity, drainage, and rainfall patterns. Decisions to treat the variability within the field have to be made in-season to accurately account for these factors in that particular growing season. These results suggest that decisions based upon historical data are based on probability, rather that certainty and that to make deliberate management decisions, information must account for the environment within the current crop year of interest.

2

Gopalapillai and Tian (1999) conducted a study using aerial color infrared imagery to correlate croip reflectance with yield potential and to identify the spatial yield pattern within a field. This study only used images collected within the growing season investigated. The in-season yield predictions had up to a 91% prediction success.

There have also been studies to show that the spatial variability that occurred in yields was based on the slope and aspect. Timlin et al. (1998) studied the effect of hillslope on both spatial and temporal corn grain yield. They found that the intra-annual differences in weather patterns had the largest effect on grain yield in fields with large hillslopes. Sloped regions drained better in ghigh rainfall years, and retained less water in drier years.

There are many proposed uses for satellite imagery in agriculture. Much historical data can be obtained from satellite imagery archives for past years, but the usefulness of this information is not clear. This study addresses the within-field variability that is detected from year to year using satellite imagery and the impact this information may have on use of satellite imagery.

3

#### MATERIALS AND METHODS

A time series of LANDSAT Thematic Mapper (TM) scenes of north-central Oklahoma,

with radiometric and geometric

corrections, spanning the period 1991 to 1999, was obtained from Earth Observation Satellites, Inc. (EOSAT). Images were georectified to US Geological Survey digital 7.5 minutes orthophoto quadrangle maps and then



Figure 1. 1998 Landsat TM image for north central Oklahoma. Taken in April.

resampled to a Universal Transverse Mercator grid with a 25 m pixel size using the nearest neighbor algorithm. An example of one of the satellite images is shown in Figure 1. The TM scenes were chosen so that, insofar as possible, the satellite overpasses occurred at or near the anthesis of winter wheat in the area (mid April to early May). In some years, cloud interference force the selection of an image slightly outside the optimum time window, and in the spring of 1995 no acceptable image was found. In 1997, clouds in the only useable image obscured some of the fields.

Six cooperators were located within the scene for the study. The locations of these fields were all in north-central Oklahoma. They were located near the towns of Red Rock, Pond Creek, Tonkawa, Cherokee, and Hitchcock, OK. Each of the field boundaries was mapped using GPS and the program Field Rover (SST Development Group, Stillwater, OK). At all sites, cropping patterns were the same for each year examined. Those fields that were grazed by cattle were grazed each year during the study period. Sites where N rates, crops, grazing, and/or tillage change from year to year were not included in this analyses. For each year's imagery, bands three and four, red and near-infrared wavelengths, were calibrated to exoatmospheric reflectance using coefficients provided by EOSAT. These reflectance values were used to calibrate the normalized difference vegetative index (NDVI), which were a measure of biomass and a prediction of grain yield. Wheat yields from the Oklahoma State University Wheat Pasture Research Unit (which is within the bounds of the satellite image) were compared to the NDVI values and a relationship between NDVI and yield was derived. A yield prediction equation was developed to estimate wheat yield of each of the cooperator fields. As a result, yield data was obtained for each 25m x 25m area in each field

Farmer cooperators' measured average yields were used to calculate the error in yield prediction for the respective fields. From 1991 to 1999, excluding years with unusable images, the yields for four of the fields were calculated using satellite imagery, and these yields were normalized based on the field average. This normalization was crucial for across year comparisons due to the error created by not having satellite images at the same stage of growth for every year. By not having the images at the same growth stages, normalizing the values by the field averages allowed comparisons to be made among years. The values compared were normalized yields, which represented relative yields of each field element compared to the average yield of the entire field for each respective year. Temporal and spatial variability appeared to be random.

5

Average yields for all possible combinations of years were calculated, e.g., combinations of 2, 3, 4, 5, and 6 years. Averages were by field element. There were 120 combinations of years, and all combinations were used for error analysis. Each average of two or more years was used as a predictor of all years' yield not used in the calculation of the average value. The error prediction based on the actual value was then calculated for each individual field element. These errors were then averaged across the entire field and the standard deviations were calculated for each prediction combination.

## RESULTS

Yearly Statistics for Each Field									
		1991	1992	1993	1994	1996	1997	1998	1999
					ma	/ha			
Pond C	reek								
	MIN	1 /	0.67	1 27	1 53	0.62	0.82	2 09	1 69
	ΜΔΧ	3 98	1 99	3.31	4.39	2 94	3.62	4 18	4.37
		2.64	1.00	2 17	2 03	1 17	1.88	3.01	3 36
	MEDIAN	2.04	1.00	2.17	2.00	1.17	1.00	2 97	3 45
	STDDEV	0.55	0.25	0.38	0.6	0.45	0.63	0.47	0.52
	CV	20.76	23.2	17.20	20.5	38 31	33.60	15 74	15 53
Dand C.	UV Kock Ecct	20.70	20.2	17.29	20.5	30.31	33.09	15.74	15.55
		0.01	0.00	0.54	0.00	0.00		0.54	0.40
		0.91	0.83	2.54	0.63	0.98		2.54	2.49
		2.67	1.67	4.93	4.64	2.8		5.02	4.7
		1.78	1.18	3.89	3.67	2.03		4.09	3.85
		1.79	1.10	3.92	3.90	2.05		4.14	3.92
	SIDDEV	0.45	0.14	0.51	0.81	0.39		0.46	0.44
	CV	25.12	11.74	13.01	21.91	19.04		11.16	11.37
Pond C	reek Wes	t							
	MIN	1.24	1.3	1.5	1.49	0.68		2.22	2.07
	MAX	2.58	2.07	4.71	3.97	2.3		4.9	4.93
	MEAN	1.84	1.71	3.65	3.26	1.64		3.94	3.65
	MEDIAN	1.81	1.7	3.78	3.34	1.69		4.01	3.66
	STDDEV	0.27	0.13	0.59	0.4	0.27		0.48	0.59
	CV	14.86	7.49	16.18	12.4	16.7		12.24	16.12
Tonkaw	a West								
	MIN	0.29	0.74	1.51		1.12	2.13		1.13
	MAX	1.04	2.41	4.06		2.44	4.38		2.53
	MEAN	0.5	1.52	3.02		1.83	3.42		1.72
	MEDIAN	0.47	1.45	3.09		1.86	3.45		1.67
	STDDEV	0.13	0.27	0.42		0.23	0.37		0.27
	CV	24.97	17.88	13.93		12.63	10.81		15.68
Cheroke	e								
	MIN	1.35	1.89	1.53	1.35	0.83	1.33	1.32	
	MAX	3.78	4.63	2.8	3.05	3.3	4.76	4.57	
	MEAN	2.49	3.69	2.16	2.43	2.38	3.91	3.39	
	MEDIAN	2.44	3.7	2.2	2.47	2.43	4.07	3.48	
	STDDEV	0.46	0.35	0.24	0.28	0.33	0.55	0.57	
	CV	18.34	9.5	11.09	11.51	13.97	14.11	16.66	
Hitchco	ck	-	-		-	-			
	MIN	0.62	0.44	1.01	0.78	0.71	1.1	0.5	
	MAX	3.15	1.49	3.56	3.92	2.9	3.92	2.41	
	MEAN	1 99	1 02	2 24	2 48	1 84	1 75	1 14	
	MEDIAN	2 02	1 08	2 24	2.52	1 85	16	1 13	
	STDDEV	0.36	0.26	0.46	0.51	0.35	0.55	0.35	
	CV	17.98	25.58	20.71	20.61	19.22	31.21	30.84	

Table 1. Statistics estimated yield values using NDVI collected from LANDSAT



Figure 2. Mean yield plot for all fields.



Figure 3. Error calculated by predicted yields with average years of historical data.

#### DISCUSSION

Coefficients of variation ranged between 16-38, 11-25, 7-17, 11-25, 10-18, and 18-31, at Red Rock, Pond Creek East, Pond Creek West, Tonkawa, Cherokee, and Hitchcock, respectively (Table 1). At each of these sites, the range in CV's almost doubled between the low to high values. A range of CV's this wide from the same fields (Figure 2.) where yield data was collected in consecutive years suggests two things. First, it says that the spatial variability was a function of the environment in which wheat was grown. In other words, the expression of spatial variability depended on the climatic conditions for the year in which the wheat was grown. This assumes that management did not vary from year to year for a specific location, which was true for each site. The only thing that changed from year to year was climate, planting date, harvest date and possible wheat variety.

Secondly, the wide range in CVs for wheat grain yield at each site implied that homogeneity in yield changed greatly from year to year. This raises the question, how could a field that was managed the same, fertilized the same, and harvested the same result in homogeneity one year and heterogeneity the next year? The wide range in CVs implied that the magnitude of the yields did not simply shift from year to year, but that the pattern of yield within a field changed from year to year.

The wide range in CVs can be partly explained by changed in average grain yield. Taylor et al., (1999) reported that as mean wheat grain yields increased, CV's decreased when observing data from 362 published wheat field experiments. When this analysis

9

was performed on the data for this study, the same conclusion could be made (Figure 1.), at least for lower yield.

In examining the prediction errors using historical data, it was apparent there were large differences in error based on the different combinations of years used for the prediction. As the number of years averaged for the prediction increased, the range of error decreased, but even after seven years of data was included, there was still an error range of 12 to 60% (Figure 2.). This showed that prediction errors could not be improved by averaging more years of historical data.

There are many factors that could have affected the variability in the fields from year to year, causing such a large range of CVs for each of the fields. Perhaps the most important of these is weather interaction with soil type and land aspect. Weather interacts in a complex way with topography and soil class to affect crop yields because of the relationships between soil relief, root growth, water retention, and nitrogen mineralization. Other factors that could affect variability are fertilizer nutrients, pH, and tillage.

#### CONCLUSIONS

What does this mean for Precision Agriculture? If the CV of a field ranges between 16 and 38%, precision agriculture technologies will have to be weather and site specific. For example, if we knew that the range of obtainable yields was 2000 to 3000 kg/ha in one year, and 2500 to 5500 kg/ha in an ensuing year, and that the distribution of that variability was spatial in nature, then management decisions relative to imputs could be drastically different from year to year. Thus, if we had an idea of how variable a site was likely to be in a given year, it would alter both actual rates and ranges of inputs very similar to that noted for the estimated yield CV. Using the CV measured during the growing season for a specific field may assist in determining the potential yield response to added nutrients (Mullen et al. 2001). Furthermore, knowledge of NDVI CV midseason for a particular field could be equated to a fertilizer response index, which various researchers have used to determine topdress fertilizer needs.

#### REFERENCES

Baier, W., 1979, Note on the terminology of crop-weather models. Agricultural Meteorology, 20, 137-145.

Bakhsh, A., T.S. Colvin, D.B. Jaynes, R.S. Kanwar, U.S. Tim. 2000. Using Soil Attributes and GIS for Interpretation of Spatial Variability in Yield. Transactions of the ASAE. 43(4): 819-828.

Gopalapillai, S. and L.F. Tian. 1999. Spatial Yield Analysis and Modeling Using Aerial CIR Images. 1999 ASAE/CSAE Annual International Meeting, Toronto. Paper No. 991151.

Mullen, R.W., K.W. Freeman, W.R. Raun, G.V. Johnson, M.L. Stone, J.B. Solie, S.M. Moges. Use of In-Season Response Index to Predict Potential Yield Increases from Applied Nitrogen. Agronomy Journal 2002.

Larson, M.H. 1986. The influence of soil series on cereal grain yield. M.S. thesis. Bozeman, Mont.: Dept. of Plant and Soil Science., Montana State University.

Taylor, S.L., M.E. Payton and W.R. Raun. 1999. Relationship between mean yield, coefficient of variation, mean square error and plot size in wheat field experiments. Commun. Soil Sci. Plant Anal. 30:1439-1447.

Thomason, W.E., W.R. Raun and G.V. Johnson. 2000. Winter wheat fertilizer nitrogen use efficiency in grain and forage production systems. J. Plant Nutr. 23:1505-1516.

CHAPTER II.

#### **INTRODUCTION**

Production agriculture has been greatly impacted by technology in the past few years, and farmers are looking at changing the way they are managing their land. Farmers have always looked at their land and managed it at different levels. Since the early 1930's, farmers have created management plans to participate in government programs showing what they were going to do with their land and incorporating their management practices to the land.

There is a tremendous amount of variability that can occur just in one farm. Certain fields may have trouble with drainage during the winter causing those fields to be unable to handle cattle grazing the wheat during the winter. Other fields may have soil that is very low in fertility creating a need for the farmer to supplement the soil nutrient level with fertilizers. There are many times that farmers have sections in a field that have pH levels that are unsuitable for crops and just those areas need treated to bring the pH back to a suitable level. Many problems like these are ones that the farmers need to understand to manage their land in the most economical fashion. These problems create a need for the farmer to look at managing smaller and smaller areas as separate entities.

#### **Precision Farming**

Precision farming is also sometimes called "site specific farming", "prescription farming, and even "variable rate application technology". All of these descriptions pertain to the tailoring of soil and crop management to match conditions at every location in a field.

15

The size of the locations which are treated differently depends on the particular application.

Two main components are needed for a precision agriculture system, the equipment and information. Some equipment typically used in precision agriculture include yield monitors, variable rate applicators, and location tracking devices (Global Positioning Systems, GPS). Information needed to build a quality precision agriculture system might include soils data, yield maps, remotely sensed data, and topographic data. Once this information is gathered, finding a relationship between these factors is key.

#### **Management Zones**

The main incentive for site-specific management is to optimize yields and economic gains for the farmer. At any location, inter-annual yield variability can also be substantial, especially under dryland farming conditions. Factors influencing yield variability include weather, topography, soil characteristics, fertility status, insect and disease pressure, cultivar selection, and agronomic practices. When all of the information is obtained, a system is needed to process and analyze the data and to display it in a meaningful fashion.

Management zones are a spatial delineation of areas that have similar soil characteristics or produce similar crop growth. It is complicated to correctly delineate management zones because there are so many factors that interact with one another to produce yield. The purpose of management zones is to improve the profitability of agricultural producers by increasing the return on crop inputs by applying them where they will be used to optimize yields. Many studies have been conducted that look at the possibility of using management zones for on-farm decisions, as well as the process of delineating those management zones. Stafford, et al (1999) used yield maps to develop management zones while McCann, et al (1996) used black and white aerial photographs to visually delineate management zones. Sudduth, et al (1996) looked at the effects of soil and landscape attributes on crop yield. They found the correlation of crop yield to soil attributes was improved by using management zones to divide the fields. These management zones were determined by analyzing topsoil depth and elevation. Fridger, et al (2000) investigated the variability of soil and landscape attributes between sub-field management zones. They found that using within field management zones for input decisions could reduce the variability of soil and landscape properties in a field over time. Kitchen, et al (1998) created management zones based on either a map overlay approach or by simple traditional soil surveys. They then used these management zones to correlate soil test parameters with yield. No measurable benefit was reported from this study.

Colvin, et al (1997) may have one of the most informative studies on the delineation of management zones and the use of historical data for on-farm decision making. They suggested that areas with consistent yield patterns could create management zones based on low, medium or high yield. In order to accomplish this, they used a ranking system, ranking each pixel in the field compared to the other pixels, from lowest to highest. Each

17

additional year's data was averaged in, and the pixels were then re-ranked. With each additional year of data, the change in rank for each individual pixel was calculated, and then summed. The overall changes in rank decreased exponentially as additional years' data was averaged in but with the trend never reaching zero. Colvin came to the conclusion that historical data is useful if the CV is low. After collecting six years of data, no stable patterns emerged for the whole field.

One of the major obstacles to the incorporation of management zones in on-farm decision making is the economic return. Farmers want to see a return on their investment, whether that is in improved yields or decreased input cost. Miller, et al (1999) lists three major issues that must be addressed in order for the use of management zones to be justified. They are 1.) that significant with-in field spatial variability of yield affecting variables must exist, 2.) that the variability can be identified and measured, and 3.) that the variability information can be used to alter management practices to increase economic return.

#### **Remote Sensing**

Researchers have developed several vegetation indices using plant reflectance. The most widely used of these indices is the normalized difference vegetative index (NDVI), (Tucker, et al 1979). NDVI is a combination of reflectance in two major portions of the spectrum, red and NIR. Red light has a low reflectance value on green vegetation because the red light is absorbed by chlorophyll in the plant for photosynthetic energy. NIR, on the other hand, is highly reflected off green vegetation due to the internal cell

structure of vegetation. NDVI is a good indicator of overall plant health. In order to look at management zones in this project, the crop reflectance was analyzed using NDVI.

The objective of this study was to attempt to harness available satellite imagery to create management zones to assist in making more accurate and timely on-farm management decisions.

#### **METHODS AND PROCEDURE**

To create management zones from historical data, we needed a strong GIS package to perform our analysis. The software used on this project was a GIS package designed specifically for precision agriculture applications. SSToolbox<sup>1</sup> is a package used by crop consultants, fertilizer dealers, educators, researchers and farm managers.

SSToolbox is a site-specific software that supports precision farming and agribusiness decision making. These software products allow users to integrate various components of precision farming technologies for analysis and decision making capabilities. SSToolbox runs on a hierarchy of data storage. The user interface of the program is very conducive to agricultural users because there is a line of command that goes from Client, to Farm, Field and Year. This allows the user to store data easily for multiple farms, fields within those farms, and individual years for each field. Once the data is stored, management decisions and input calculations can be based on an area within the field, the whole field, or the whole farm. Producers can look at their total input and total output for their entire business. The program utilizes ArcView V3.2 as the main GIS platform, while using Surfer software (Golden Software, Golden, CO) to allow raster/vector conversions. (SST Development Group 2000, Stillwater, OK)

The following is a list of procedural steps that had to be performed to acquire a final product that was meaningful to the producer:

#### 1. Obtain georeferenced field boundaries.

Use GPS integrated in Field Rover Software, created by SST Development Group, to acquire a vector polygon file that is representative of the field boundary in question. By using a software that allows the user to define vertices using GPS input and then creates a polygon with these indices, a shapefile is created that can be imported into ArcView based software. Field Rover would also allow the user to create scouting and sampling operations.

#### 2. Satellite Data was obtained for each year for each field.

A time series of LANDSAT Thematic Mapper (T.M.) scenes of north-central Oklahoma, spanning the period 1991 to 1999 (Figure 4.), were obtained from EOSAT, now Space Imagery, with radiometric and geometric corrections. (Table 2)



Figure 4. 1998 Landsat TM image for north central Oklahoma. Taken on April 23

Year	1991	1992	1993	1994	1996	1997	1998	1999
Scene	April 4	May 9	April 25	March 27	April 2	April 20	April 23	May 12
Date								

 Table 2. Dates of the Landsat Thematic Mapper scenes used in the study.

<sup>&</sup>lt;sup>1</sup> SSToolbox, Version 3.2, Site Specific Technologies, Stillwater, OK

The images were georectified with US Geological Survey digital 7.5 minutes orthophoto quadrangle maps and then resampled to a Universal Tranverse Mercator grid, with a 25 m pixel size using the nearest neighbor resampling algorithm. An example of one of the satellite images is shown in Figure 2. The TM scenes were chosen so that, insofar as possible, the satellite overpasses occurred at or near the heading stage of winter wheat in the area (mid April to early May). In some years, cloud interference force the selection of an image slightly outside the optimum time window, and in the spring of 1995 no acceptable image was found.

#### 3. Convert satellite raster data to vector point data for calculation purposes.

The satellite data had to be converted from a digital raster grid format to vector point data using a function within SSToolbox. There is an option within toolbox that handles image files and will convert image files to point data. Using this method, the digital numbers are extracted from the image for only the area within the field boundary. (Figure 5.) This decreases the amount of data that must be stored for each image.



Figure 5. Satellite image for OSU Wheat Pasture research center before and after raster to vector conversion process.

#### 4. Create buffer zones for each field.

A buffer zone was created inside the field boundary and around known non-cropped areas within the fields (oilwells, tanks, etc.) with a width of one pixel (25 meters). Using masking techniques, only the point data within the field excluding points contained within the buffer zone were selected. Only these selected points were used for yield calculations. This decreased interference due to edges of the field and georeferencing error within the satellite image.

#### 5. Calculate reflectance value for red and near infrared wavelengths.

To calculate the reflectance values, the digital numbers for the red and NIR bands were corrected for non-surface factors such as sensor detector calibration and geometry, sun angle and earth-sun distance. I performed this task within SSToolbox software. These corrected the pixel values to exoatmospheric reflectance values.

#### 6. Calculate NDVI for all pixels in each field.

NDVI has been widely used as an indirect measure of crop biomass and yield. NDVI is calculated from the reflectance values of the red and near infrared (NIR) wavelength bands, using the following equation:

$$NDVI = \frac{(NIR - \text{Re}d)}{(NIR + \text{Re}d)}$$
 Equation 1. NDVI Calculation

Any relationship between vegetation index and yield is based on the assumption that the vegetation index measures crop parameters directly linked with the yield. NDVI utilizes

the large spectral difference in the red and near infrared band reflectance of living vegetation. As the green biomass of the canopy increases, reflectance in the red band portion of the spectrum decreases, due to the absorbance for photosynthesis, while that in the near infrared band increases due to the internal structure of the leaves. The accumulated dry matter of a given crop at a given stage of growth is the result of the crop carbon dioxide intake, soil moisture uptake and net photosynthetic assimilation. Since the NDVI is a measure of the photosynthetic potential of the vegetation, it is indirectly related to the crop yield and thus is suitable for yield estimation.

In order to calculate the NDVI, the theme table for the point data from the satellite imagery reflectance measurements was used. The table was then opened for editing and the calculate field function was used to complete the calculation of NDVI for each field.

#### 7. Calculate predicted yield

The predicted yield was calculated by using a model developed by Itenfisu, et al (1999).



In order to create this model, four cloud-free TM images from 1993, 1997, 1998 and 1999 were analyzed over the Oklahoma State University Wheat Pasture Research Unit located near Marshall, Oklahoma (Figure 6.). The Wheat Pasture Research Unit was divided Figure 6. Satellite image of OSU Wheat

Pasture Research Center with paddock boundaries.

into paddocks that were planted to hard red winter wheat (*Triticum aestivum* L.). Average winter wheat grain yield for each paddock in the research farm were measured for those years. Average yield was determined by measuring yield from 2 passes of a 3 meter wide plot combine extending the length of the paddock. For a given year, the average NDVI within a paddock was calculated by carefully selecting the pixels that fell within the harvested area. A scatter plot of the average NDVI for each paddock against the corresponding average grain yield for the four years data indicated that a simple exponential model could be used to define the relationship between grain yield and average reflectance NDVI. Since there were no significant differences among the four years of NDVI and grain yield data, a single exponential calibration equation was fitted to the four years of data. The exponential equation follows:

Y=165.9*e*<sup>4.0443NDVI</sup> Equation 2. Exponential Yield Prediction Equation

Y is wheat grain yield in kg ha<sup>-1</sup>. (Figure 7.)The adjusted  $R^2$  for the fitted equation was 0.78. This equation was then used for each respective field for each year to calculate predicted yield. The curve was fitted with Table Curve 2D version 4 (SPSS software).



Figure 7. The correlation between the satellite image NDVI and the predicted yield.

#### 8. Normalize each pixel by field average.

The predicted yield values for each of the pixels were normalized to the field average so that the pixel values would be a reference to the relative value of that pixel compared to the average of the field. The normalization was calculated by dividing the individual pixel value by the average of the values throughout the field. This allowed cross-comparisons across multiple years. The normalized NDVI maps provide the farmers a quantitative tool to understand how the field is performing. Likewise, the normalization by average yield enabled us to remove the effects of rainfall and other factors on the magnitude of the biomass and subsequent grain yield, while enabling us to focus on the relative effects of those factors. Another factor that could be eliminated by normalizing the yield across the fields was the differences in satellite imagery acquisition.
### 9. Convert vector point data to raster grid surface.

The vector point data for each year was converted into a raster surface using an interface with Surfer software. To convert from the vector model to a raster grid surface, an interpolation method, nearest neighbor, was used to assign values to each grid cell. The method that was used for this study was a nearest neighbor interpolation with a search radius equal to the original satellite resolution of 25 m.

### 10. Create megasurface of all normalized yield data.

After raster surfaces were created for each year, the normalized yield for each year was merged into one megasurface. The yields were normalized due to variances in conditions and timing of the satellite imagery each year. This megasurface allowed for calculations and comparisons to be made for each location in the field across years.

#### 11. Perform calculations on normalized yields.

Normalized yields for each year were averaged to create a surface of average normalized yields across years. This gives a historical look at how the field has performed. In order to represent the temporal variability for each position in the field, the coefficient of variation and the standard deviation were calculated for each pixel across the eight years of data.

### 12. Create management zones using established criteria.

Management zones were created within each field using multiple criteria. In researching which criteria should be chosen, many different ones were attempted before a final

criteria was determined. Criteria using standard deviations, natural breaks, equal intervals, as well as many others were used before the following criteria was chosen as not only one that fit most fields most accurately, but it was also a simple criteria that could be understood by the majority of producers. The criteria that fit most fields was the following:

> <u>Area Above Average Field Yield</u> CV < 0.3 Average Normalized Yield > 110%

<u>Area Average</u> CV < 0.3 Average Normalized Yield < 100% and > 90%

Area Below Average Field Yield CV < 0.3 Average Normalized Yield < 90%

Area Inconsistent (No determination made) CV > 0.3

This was performed using Boolean operations within the query of the megasurface data table. The desired areas were selected then assigned a value of 1 to 4 respectively. These values were then used to create a map of the surface showing the management zones. These management zones are the final product for the producer to use.

To begin the process of using this data set as a management tool for farmers, farmers participating in the study were approached and introduced to the idea of using satellite images to detect variability occurring in each field. The farmers were presented with satellite images from each year for their respective field, map of each year's normalized NDVI and predicted yields, and an averaged normalized NDVI map for all years combined. (These maps and images can be found in the appendix AA - AE.) Even though all of this information was gathered and analyzed, conclusions as to what was happening in each field could not be determined without the interaction with the farmer. Some other tools that were utilized in the analysis of these images were soils surveys, aerial photographs, and field historical management information from the farmers. By looking at the soil surveys, we could see some distinct patterns in yield variability that could be attributed to changes in soil type. Another piece of information that was crucial to deciding if the management zones were useful for decision-making was the field historical management information.

## **RESULTS AND DISCUSSION**

When we normalized the estimated yields (divided the yield for each pixel by the average estimated yield for the farm), we discovered that the farm where the yield patterns persisted across years exhibited large differences between regions of high yield and regions of low yields. The region with high yield was a creek bottom and the soil was a Port silt loam. The region with the consistently low yield was also associated with a soil type, but the soil type was misclassified as Port silt loam. That soil was obviously poor. The intermediate yielding soils also had some areas of low yielding soil, but these areas were small enough that they were not designated on the soil map. This and similar farms could be divided into management zones based on normalized yields, averaged over five to six years. Each region can be soil sampled and managed differently from its neighbors.

### **By Field Analysis**

To begin the process of using this data set as a management tool for farmers, the farmers participating in the study were approached and introduced to the idea of using satellite images to detect variability occurring in each field. The farmers were presented with satellite images from each year for their respective field, maps of each year's normalized NDVI and predicted yields, and an average normalized NDVI map for all years combined. Other tools utilized in management decision making were soil surveys, aerial photographs, and field historical management information. Even though all of this information was gathered and analyzed, conclusions as to what was happening in each field could not be determined without the input from the farmer.

30

### **Tonkawa West Farm**

The Tonkawa West farm was a 151 acre field that was split into two sections by a drainage ditch. As shown in the aerial photo in Figure 8., the east portion of the field was inaccessible from the west part of the field because of a drainage ditch. The cooperating farmer described management decisions made for the years of interest. Yield on the east portion of the field was consistently lower, even with the same management practices. That area had greater slope and was more eroded than the west part



Figure 8. Tonkawa West farm aerial imagery and average normalized yields over six year period.

of the field, although the soils had the same classification. After considering different options, the farmer decided to split the field into two smaller fields (management units)

using the drainage way through the northeast portion of the field as the dividing line. The field used two different management zones to try to maximize the yield in the economic returns for the area. The farmer practiced this for the next year and reported later that he believed he had better overall returns on the field as a whole due to this change in management practice.



Figure 9. Tonkawa West farm 1993 corrected yield.

Another benefit of the satellite imagery is the ability to see the effect of management decision. In 1993, the Tonkawa West farm was treated for cheat, a highly competitive weed in wheat, with herbicide applied to the west portion of the field but not to the east portion of the field. By looking at the satellite imagery for that year (Figure 9.), the

benefit of the herbicide application was visually evident with a dramatic increase in yield (35 bu/ac to 50 bu/ac).

### **Red Rock Farm**

The Red Rock farm was a 58 acre field that displayed persistent NDVI patterns over the years examined (Figure 10.). When normalized NDVI averaged over years was paired with the soil survey and the aerial photograph, it was found that there were some distinct patterns related to the soils and terraces in the field. The northwest corner of the field consistently yielded higher than the whole field. Yield varied between years because the area flooded with heavy rains due to poor drainage from the county road. The farmer might be able to his economic returns by treating the southern area of the field differently than the northern area of the field, to treat the area around the waterway as a lower yielding area, and to intensify the management inputs in the higher yielding area.



Figure 10. Red Rock farm aerial imagery and normalized average estimated yields.

The southern corner of the field was misclassified as a class I soil type that is similar to the northwest corner of the field. This area consistently yielded lower than the rest of the field as indicated by NDVI. The farmer is considering not fertilizing this area because of its low yield potential. Although the one area was misclassified, the average NDVI maps closely corresponded to the soils map. (Figure 11) In this case, managing by soil classes is a useful practice. The management decision that could be implemented on this farm would be to split the high yielding areas and treat them differently than the low yielding areas. The farmer could look at the normalized NDVI map and the soils map to see the best way to separate the field into three management zones, high, average, and low yielding. It would be possible that the best decision would be to plant the southern end of the field to grass and not crop that area.



Figure 11. Correspondence of Red Rock farm soils map to average normalized yield over years.

## **Hitchcock Farm**

One of the interesting farms studied was in Hitchcock, Oklahoma. The soils map showed the same soils in most of the east and west fields (Figure 12.). The west field has

Consistently higher normalized NDVI values from year to year.



Figure 12. Hitchcock farm average normalized yield over six years of data.

# Hitchcock, OK - Soil Survey



### Figure 13. Hitchcock farm soil classification illustration.

The farmer informed us that the west field was broken out of its prairie state in the early 1970's while the east field was farmed since the late 1890's. There was about 75 years more depletion of organic matter and nutrients in the west field. The average normalized NDVI yields for the seven years quantified this problem for the farmer. He had known

that the east field had become relatively lower yielding than the west field. However, interpreting satellite images gave a visual and quantitative measure of the variability occurring in the fields. Strategic soil sampling was planned by Roger Gribble, OSU Northwest Area Extension Agronomist, to check the organic matter content and the pH of the soils in both fields to diagnose the causes of the lower yields in the east field.

## **Carrier Farm**

The farm in Carrier, OK, gave a unique perspective of how the normalized NDVI images would be able to help determine the loss due to natural disasters. The Carrier farm was divided into smaller fields for the purpose of producing seed wheat for sale. (Figure 14.) This created a situation where different wheat varieties were planted in each field in each year.



Figure 14. Aerial image of Carrier farm's fields.



Figure 15. Carrier farm average normalized yields after 7 years of data.



Figure 16. 1992 Carrier farm yield surface.

In 1992, there was an outbreak of disease in the wheat; the wheat in the large southwest field was not a disease resistant variety and the wheat in the large southeast field was resistant. (Figure 16.) In mid-season, the loss of yield could be seen by a drastic lag in the yield values in the non-resistant field.



Figure 17. Carrier farm illustration of hail damage line from 1999 storm.

In 1999, there was another natural disaster that reduced the yield in some fields. (Figure 17) A hailstorm came through the area and one could see the distinct edge of the storm as it moved through the fields. With the satellite image and the NDVI map, a more accurate assessment of the loss could be made. One could see the damage incurred by the hail earlier in the season would not have to wait until harvest to determine the economic loss.

# CONCLUSIONS

The satellite imagery is a tool that can be utilized by farmers to enhance their management decision. By normalizing the NDVI data by the field average, comparisons can be made across years to create a historical reference of the field's performance for the farmer to visualize.

There are many things that a producer should consider before making a decision to use a new technology. There are cases when management at smaller than field scale can be justified. In these cases, tools such as soil maps and satellite imagery can be useful, but one must consider the cost benefit of each technology. The fields that are high yielding with class I soils should be managed on the farm level, because smaller than field scale management would not make enough difference to pay for itself. With the current condition of wheat prices, many of these technologies may not be economical due to the data analysis that would need to occur to come to a decision. Higher value crops may benefit more from this technology.

The degree of variability in crop productivity within a farm can be incredibly diverse. Assessment of crop productivity variability requires two things: the knowledge of the production level and the area under production. Information on the status of crops within a farm is spatial in nature. A farmer's traditional method of assessing crop conditions is through experience and knowledge of topography, soils and weeds, and therefore tends to lack systematic organization and to be more qualitative than quantitative. Therefore, this

40

approach to assessment is limited in its content and lacks precision, especially for farms of relatively large size.

Satellite remote sensing data, such as Landsat TM imagery, is a tool that can be used today, by farmers to asses the crop condition in season and in a relatively timely fashion. The Landsat TM imagery allows a farmer to see the variability in the condition of the field using NDVI as a measure of the variability of the field. The farmer, using this information, is able to compare differences in productivity in different areas of the field. When farmers are presented with images and maps of their farms, their own knowledge of the production of the field frequently provides insight or identifies trends and anomalies in the satellite image. The insight from the farmer allows probable causes of variability to be identified more readily. It also allows the farmer to see the impact of the variability and the magnitude of impact that the variability on performance of the crop in the field. When multiple years of data are combined, historical quantification of the level of productivity in areas within a farm, along with the spatial variability, can be a very strong informational tool.

A principal goal of precision agriculture is to select practical agricultural management practices that treat each unit area of the farm based on its needs so that returns are maximized in an environmentally friendly manner. Landsat imagery data can play a key role in the attempt to understand crop production variability within a given farm and come up with farm management alternatives that consider the variability.

41

Farmers are knowledgeable about the variability occurring within their fields. With the introduction of normalized NDVI maps, though, the farmer can observe the magnitude of that variability and how it occurs spatially. When yield predictions were attempted, there was a very large spread in the data and the accuracy was moderate.

There were many years the yield predictions were very close to the average, but there were also many years when the predictions were inaccurate. In years that drought stress occurred early in the season and timely rains occurred right at flowering, there was a very large grain yield in spite of low plant biomass. There were years when the prediction was too high due to factors occurring late in the growing season. NDVI is a very good predictor of plant biomass and may be a better indicator of plant nutrient need and variability, as opposed to yield prediction. By normalizing the NDVI data by the field average, comparisons can be made across years to create a historical reference of the field's performance for the farmer to visualize.

# REFERENCES

- Bakhsh, A., T.S. Colvin, D.B. Jaynes, R.S. Kanwar, U.S. Tim. 2000. Using soil attributes and GIS for interpretation of spatial variability in yield. Transaction of the ASAE, Vol 43(4): 819-828.
- Colvin, T.S., D.B. Jaynes, D.L. Karlen, D.A. Laird, J.R. Ambuel. 1997. Yield variability within a central Iowa field. Transactions of ASAE; Vol 40(4):883-889, April 1997.
- Fridgen, J.J., N.R. Kitchen, K.A. Sudduth. 2000. Variability of soil and landscape attributes within sub-field management zones. In: Proceedings of the Fifth International Conference on Precision Agriculture. American Society of Agronomy, Madison, WI.
- Itenfisu, D., R.L. Elliott, J.B. Solie, and E.G. Krenzer. 199. Assessing wheat yield variability using satellite remote sensing. In: Proceedings of the Pecora 14/Land Satellite Information III: 6-10 December 1999, Denver, CO.
- Kitchen, N.R., K.A. Sudduth, and S.T. Drummond. 1998. An evaluation of methods for determining site-specific management zones. In: Proceedings of North Central Extension – Industry Soil Fertility Conference, St. Louis, MO. 11-12Nov. 1998. Potash and Phosphate Institute, Brookings, SD.
- McCann, B.L., D.J. Pennoch, C. van Kessel, F.L. Walley. 1996. The development of management units for site specific farming. In: Proceedings of the Third International Conference on Precision Agriculture. American Society of Agronomy, Madison, WI. Pp295-302.
- Miller, R.D., S. Pettygrove, R.F. Denison, L. Jackson, M. Cahn, R. Plant, T. Kearny. 1999. Site specific relationships among flag leaf nitrogen, SPAD meter values and grain protein in irrigated wheat. In: Proceedings of the Fourth International Conference on Precision Agriculture. American Society of Agronomy, Madison, WI. Pp113-122.
- Stafford, J.V., R.M. Lark, H.C. Bolam. 1999. Using yield maps to regionalize fields into potential management units. In: Proceedings of the Fourth International Conference on Precision Agriculture. American Society of Agronomy, Madison, WI. Pp 225-238.
- Sudduth, K.A., N.R. Kitchen, D.F. Hughes and S.T. Drummond. 1996. Analysis of spatial factors influencing crop yield. In: Proceedings of the Third International Conference on Precision Agriculture. American Society of Agronomy, Madison, WI.

Tucker, C.J. (1979). Red and photographic infrared linear combination for monitoring vegetation. Remote Sensing Environment. 8, 127-150

# APPENDIX A

# **CARRIER FARM**



Figure 18. Example of satellite imagery of Carrier farm, accquisition date of April 23, 1998.



Figure 19. Carrier farm 1991 predicted yield (bu/ac) surface. Effects of grazing can be seen in lower yield prediction areas.



Figure 20. Carrier farm 1992 predicted yield (bu/ac) surface. Disease affected the yield predictions in three of the fields.



Figure 21. Carrier farm 1993 predicted yield (bu/ac) surface. Standing water lowered yield potential in southern areas of the farm.



Figure 22. Carrier farm 1994 predicted yield (bu/ac) surface



Figure 23. Carrier farm 1996 predicted yield (bu/ac) surface



Figure 24. Carrier farm 1998 predicted yield (bu/ac) surface. One field was not planted.



Figure 25. Carrier farm 1999 predicted yield (bu/ac) surface. Effects of hail damage can be seen in the northern fields.



Figure 26. Carrier farm average normalized yield raster surface

# **APPENDIX B**

# **CHEROKEE FARM**



Figure 27. Example of Cherokee farm satellite imagery, image acquired on April 28, 1998.



Figure 28. Cherokee farm 1991 predicted yield (bu/ac) raster surface.



Figure 29. Cherokee farm 1993 predicted yield (bu/ac) raster surface.



Figure 30. Cherokee farm 1994 predicted yield (bu/ac) raster surface.



Figure 31. Cherokee farm 1996 predicted yield (bu/ac) raster surface.



Figure 32. Cherokee farm 1997 predicted yield (bu/ac) raster surface.



Figure 33. Cherokee farm 1998 predicted yield (bu/ac) raster surface.


Figure 34. Cherokee Farm 1999 predicted yield (bu/ac) raster surface.



Figure 35. Cherokee farm average normalized yields divided into management zones.

# APPENDIX C

## HITCHCOCK FARM



Figure 36. Hitchcock farm 1992 predicted yield (bu/ac) raster surface.



Figure 37. Hitchcock farm 1993 predicted yield (bu/ac) raster surface.



Figure 38. Hitchcock farm 1994 predicted yield (bu/ac) raster surface.



Figure 39. Hitchcock farm 1996 predicted yield (bu/ac) raster surface



Figure 40. Hitchcock farm 1998 predicted yield (bu/ac) raster surface.



Figure 41. Hitchcock farm 1999 predicted yield (bu/ac) raster surface.



Figure 42. Hitchcock farm average normalized yield, from six years of data, divided into management zones.

## APPENDIX D

# **RED ROCK FARM**



Figure 43. Example of Red Rock farm satellite imagery, acquired on April 28, 1998.



Figure 44. Red Rock farm 1991 predicted yield (bu/ac) raster surface.



Figure 45. Red Rock farm 1992 predicted yield (bu/ac) raster surface.



Figure 46. Red Rock farm 1993 predicted yield (bu/ac) raster surface.



Figure 47. Red Rock farm 1994 predicted yield (bu/ac) raster surface.



Figure 48. Red Rock farm 1996 predicted yield (bu/ac) raster surface.



Figure 49. Red Rock farm 1997 predicted yield (bu/ac) raster surface.



Figure 50. Red Rock farm 1998 predicted yield (bu/ac) raster surface.



Figure 51. Red Rock farm 1999 predicted yield (bu/ac) raster surface.



Figure 52. Red Rock farm average normalized yield surface, divided into management zones.

### **APPENDIX E**

### TONKAWA WEST FARM



Figure 53. Example of Tonkawa West farm satellite imagery, acquired April 28, 1998.



Figure 54. Tonkawa West 1991 predicted yield surface (bu/ac) raster surface.



Figure 55. Tonkawa West farm 1992 predicted yield (bu/ac) raster surface.



Figure 56. Tonkawa West 1993 predicted yield (bu/ac) raster surface.



Figure 57. Tonkawa West farm 1996 predicted yield (bu/ac) raster surface.



Figure 58. Tonkawa West farm 1997 predicted yield (bu/ac) raster surface.



Figure 59. Tonkawa West farm 1998 predicted yield (bu/ac) raster surface.



Figure 60. Tonkawa West farm 1999 predicted yield (bu/ac) raster surface.



Figure 61. Tonkawa West farm average normalized yield surface, divided into management zones.

### VITA

### Carly Nicole Washmon

#### Candidate for the Degree of

### Master of Science

### Thesis: USING HISTORICAL LANDSAT TM SATELLITE IMAGERY FOR ON-FARM MANAGEMENT DECISION IN HARD RED WINTER WHEAT.

Major Field: Biosystems Engineering

**Biographical:** 

- Personal Data: Born in Woodward, Oklahoma, May 11, 1977, daughter of Sandra M. Washmon and the late Jimmy Dean Washmon
- Education: Graduated from Woodward High School, Woodward, Oklahoma, in May 1995; received Bachelor of Science in Biosystems Engineering from Oklahoma State University in December 1999; completed requirements for the Masters of Science Degree in Biosystems Engineering at Oklahoma State University in December, 2003.
- Professional Experience: Research Engineer, Department of Biosystems and Agricultural Engineering, Oklahoma State University, May 2000-July 2002; Application and Sales Engineer, NTech Industries, Inc., July 2002-July2003; Programs Administrator, Oklahoma Department of Agricultural, Division of Plant, Industry and Consumer Services, November 2003 – Present.

Name: Carly Nicole Washmon

Date of Degree: July, 2005

Institution: Oklahoma State University

Location: Stillwater, Oklahoma

Title of Study: USING HISTORICAL LANDSAT TM SATELLITE IMAGERY FOR ON-FARM MANAGEMENTDECISIONS IN HARD REDWINTER WHEAT

Pages in Study: 93

Candidate for the Degree of Master of Science

Major Field: Biosystems Engineering

Scope and Method of Study:

Wheat grain yields from selected fields in Oklahoma were monitored over a nine-year period using satellite imagery. Yields for each 25m x 25 m area within each field were estimated from NDVI measurements obtained from LANDSAT scenes in north-central Oklahoma. Statistics were gathered from these locations from 1991 to 1999.

Findings and Conclusions:

Wheat grain yield levels are known to vary from one year to the next and much of this variability is often attributed to climatic differences from year to year. However, within field variability of wheat grain yields as a function of time has not been extensively evaluated. This project discusses the variability in those yields seen from year to year, as well as the variation within the fields each year. This information is then used to analyze the use of satellite imagery and historical yield as a tool for on-farm management decisions.