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Daniel Unger
Arthur Temple College of Forestry and Agriculture, Stephen F. Austin State University, unger@sfasu.edu

I-Kuai Hung
Arthur Temple College of Forestry and Agriculture, Stephen F. Austin State University, hungi@sfasu.edu

Kenneth W. Farrish
Arthur Temple College of Forestry and Agriculture, Stephen F. Austin State University, kfarrish@sfasu.edu

Darinda Dans
Arthur Temple College of Forestry and Agriculture, Stephen F. Austin State University

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Daniel Unger, Division of Environmental Science at Arthur Temple College of Forestry and Agriculture, Stephen F. Austin State University, Nacogdoches, TX, USA

I-Kuai Hung, Division of Environmental Science at Arthur Temple College of Forestry and Agriculture, Stephen F. Austin State University, Nacogdoches, TX, USA

Kenneth Farrish, Division of Environmental Science at Arthur Temple College of Forestry and Agriculture, Stephen F. Austin State University, Nacogdoches, TX, USA

Darinda Dans, Division of Environmental Science at Arthur Temple College of Forestry and Agriculture, Stephen F. Austin State University, Nacogdoches, TX, USA

ABSTRACT

The Haynesville Shale lies under areas of Louisiana and Texas and is one of the largest gas plays in the U.S. Encompassing approximately 2.9 million ha, this area has been subject to intensive exploration for oil and gas, while over 90% of it has traditionally been used for forestry and agriculture. In order to detect the landscape change in the past few decades, Landsat Thematic Mapper (TM) imagery for six years (1984, 1989, 1994, 2000, 2006, and 2011) was acquired. Unsupervised classifications were performed to classify each image into four cover types: agriculture, forest, well pad, and other. Change detection was then conducted between two classified maps of different years for a time series analysis. Finally, landscape metrics were calculated to assess landscape fragmentation. The overall classification accuracy ranged from 84.7% to 88.3%. The total amount of land cover change from 1984 to 2011 was 24%, with 0.9% of agricultural land and 0.4% of forest land changed to well pads. The results of Patch-Per-Unit area (PPU) index indicated that the well pad class was highly fragmented, while agriculture (4.4-8.6 per sq km) consistently showed a higher magnitude of fragmentation than forest (0.8-1.4 per sq km).

Keywords: *Change Detection, Land Cover Change, Landsat, Landscape Metrics, Remote Sensing, Surface Disturbance*

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1. INTRODUCTION

Oil and natural gas exploration has increased substantially in recent years due to increased demand and improvements in technologies that allow for access to geologic strata once considered impractical to pursue for petroleum. With the increases in oil and gas activities comes a conversion of land cover, such as forest or agricultural land, to oil and gas well pads. This disturbance of land can fragment the land cover and result in loss of productive forests and agricultural lands, and may affect other resources, such as water resources and wildlife habitats.

During oil and gas development, a complex system of well pads, roads, pipelines, and other infrastructure is created across the landscape. Louisiana and Texas have experienced an increase in natural gas exploration due to recent advances involving hydrofracturing and horizontal drilling. Currently, one of the largest and most active gas plays in the United States is in the Haynesville Shale formation, which is located in northwest Louisiana and northeast Texas.

The Haynesville Shale region encompasses approximately 2.9 million hectares, and has been subject to intensive exploration. The full spatial extent of the Haynesville Shale is not yet known and the mapped region is continually changing due to new discoveries. The Haynesville Shale lies in an area that has had significant oil and gas development due to the Louisiana-Mississippi Salt Basins and the East Texas Basin (Grant et al., 2009). Oil and gas exploration also continues that is not related to the Haynesville Shale, so identification of wells specific to the Haynesville Shale is based on drilling depth and composition of the gas produced (Grant et al., 2009).

Land cover changes are continually occurring due to natural and anthropogenic activities, and monitoring of natural resources has been significantly enhanced with improvements in satellite imagery. With the availability of sequential satellite imagery, temporal changes on the Earth's surface may be evaluated. Land cover change detection has been applied in various situations, and is especially useful in monitoring changes due to human impact (Bi et al., 2011; Phalke & Couloigner, 2005; Tang et al., 2008; Vescovi et al., 2002).

Change detection is a valuable tool for analyzing biophysical and anthropogenic alterations to the Earth's surface. Change detection is the process of identifying differences by viewing an image of a specific location at different times. Examples of uses for change detection are land-use and land-cover changes, forest or vegetation changes, environmental change, and urban change (Lu et al., 2004).

One method for change detection is post-classification comparison. Using post-classification of images to detect change has been successful, since it better handles effects of bias and variance between images (Phalke & Couloigner, 2005). Post-classification comparison of Landsat Thematic Mapper (TM) imagery has shown to be a successful method for change detection and quantification of the changes (Döner, 2011; Vescovi et al., 2002; Zhao et al., 2004). With the use of Landsat TM imagery, changes over time to forests and agricultural lands due to oil and gas well pads may be quantified within the Haynesville Shale region.

Changes due to abrupt and gradual disturbances to land surfaces are in need of investigation. Surface disturbance is caused by distinct events that alter the physical environment (Farina, 1998). This can lead to fragmentation, which is a continuous process that subdivides the land cover into smaller, isolated patches (Farina, 1998; Li et al., 2009). Abrupt change is caused by a disturbance, such as well pads, while gradual change is a linear trend due to something like long-term annual rainfall or land degradation (Verbesselt et al., 2010). Disturbance of land from petroleum exploration and production may result in a fragmented landscape.

Concerns associated with fragmented landscapes include ecological and economic issues. Ecological concerns include wildlife habitat loss, shifts in species distribution, and increased soil erosion. Economic issues include the loss of land used for other resources (e.g., timber or crops) and loss of recreational uses (e.g., hunting and fishing).

Land cover metrics can be used to quantify the land cover patterns and assess possible fragmentation due to well pads. Two metrics useful for the quantification of fragmentation are the Patch-Per-Unit area (PPU) and Square Pixel (SqP). Patch-Per-Unit area is the degree of fragmentation of patches and SqP is a measurement of the shape complexity of patches (Ayad, 2005; Franklin & Dickson, 2001). The inclusion of land cover metrics provides further information to assess the impact oil and gas well pads have on landscape dynamics.

Due to disturbances of the land, oil and gas exploration and production has shown a range of negative impacts on the landscape (Bi et al., 2011; Wilbert et al., 2008). By calculating the physical dimensions of the disturbed area, direct effects can be measured (Wilbert et al., 2008). Land cover metrics are used to quantify the composition and spatial arrangement of the Earth's surface. Advantages of the use of metrics include a better capturing of the inherent spatial structure of the land cover patterns and biophysical characteristics of the spatial dynamic (Tang et al., 2008). Disturbed land cover size-shape relationships can influence multiple environmental aspects, including surface water runoff and animal dispersal (Krummel et al., 1987).

The overall objective of this study was to quantify the amount of land within the Haynesville Shale area that had been converted from forest land and agricultural land to oil and gas well pads. Oil and gas exploration activity was high in Louisiana and Texas in the 1980s and spiked again in recent years. A 27-year period was assessed to quantify changes in land cover due to oil and gas exploration and production from 1984 to 2011 and for 6 different year comparisons within the 27-year period. The land cover changes were also assessed through landscape metrics calculations.

2. METHODS

2.1. Study Area

The study area was the region located above a natural gas producing shale known as the Haynesville Shale located in northwest Louisiana and northeast Texas (Figure 1). The boundary of the study area was set based on a shapefile available from the Department of Energy's Energy Information Administration (ftp://ftp.eia.doe.gov/pub/oil_gas/natural_gas/analysis_publications/maps/maps.htm, May 2011). The Haynesville Shale lies under nine Louisiana parishes (Bienville, Bossier, Caddo, Claiborne, DeSoto, Natchitoches, Red River, Sabine, and Webster) and sixteen Texas counties (Angelina, Cherokee, Gregg, Harrison, Jasper, Marion, Nacogdoches, Panola, Polk, Rusk, Sabine, San Augustine, Shelby, Smith, Tyler and Upshur). Land cover of this region contains large amounts of forest and agricultural land.

2.2. Image Acquisition

Landsat 5 TM images were obtained through the United States Geological Survey (USGS) Global Visualization Viewer (GloVis) website (http://glovis.usgs.gov, November 2011). Images acquired for the study area included path 24, rows 37 and 38, and path 25, rows 37 and 38 (Table 1). Since four Landsat images were required for complete coverage of the study area, a mosaic image was created for each date using ERDAS IMAGINE 2010 (Version 10.1; ERDAS Inc., Norcross, GA, USA). The mosaicked images had minimum cloud cover.

2.3. Radiometric Correction

Landsat TM bands were chosen to avoid atmospheric effects due to absorption, so the primary atmospheric effect in the data was due to scattering. All data were attained at 8-bit radiometric resolution. Additionally, the use of cloud-free images acquired at approximately the same time of year reduced possible environmental effects.

Figure 1. The Haynesville Shale region in Louisiana and Texas

A radiometric correction was performed on each image to reduce errors that may have been present from the sensor or the atmosphere. Histogram subtraction of each band was used for radiometric correction. For each band, the minimum digital value was subtracted per pixel. These lowest digital values represented atmospheric effects, and were altered to show a more accurate spectral signature resulting in improved classification accuracy.

2.4. Geometric Correction

The Landsat 5 TM images were already geometrically corrected when downloaded from USGS GloVis. Each image was geometrically referenced to the World Geodetic System (WGS) 1984, Universal Transverse Mercator (UTM) Zone 15 North.

2.5. Image Classification

Each individual satellite image in the time series was classified to their respective land cover types using ERDAS IMAGINE 2010 software. Unsupervised classification was used with 500 classes, 100 iterations, and a 0.975 convergence threshold. Each class was identified and recoded to its respective land cover type (forest land, agricultural land, well pad, or “other”). Forest land included deciduous and evergreen, agricultural land included cropland and pasture, and the “other” class included everything not classified as forest land, agricultural land, or well pads, such as water, roads, and buildings.

Well pads did not have a unique spectral digital signature. Agricultural land and urban areas were misclassified periodically as well pads. Consequently, each pixel value that was classified as well pad was examined visually to determine if it also represented another class. In all instances, the pixel value was representative

Table 1. Landsat 5 TM imagery used for this study

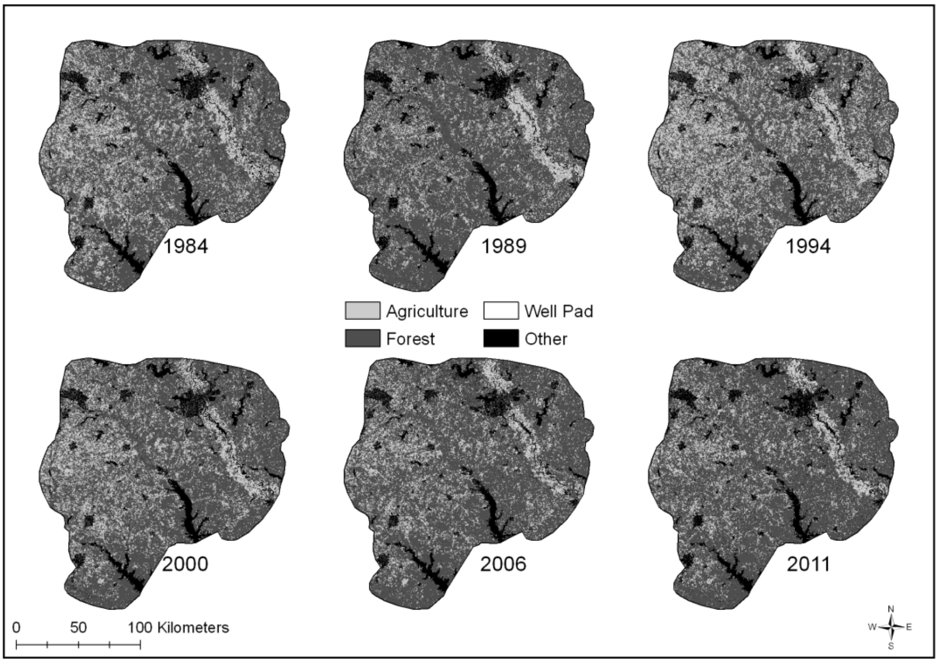
Year	Date	Path/Row
1984	30 November 1984 30 November 1984 21 November 1984 21 November 1984	24/37 24/38 25/37 25/38
1989	12 November 1989 12 November 1989 03 November 1989 03 November 1989	24/37 24/38 25/37 25/38
1994	31 March 1994 31 March 1994 07 April 1994 07 April 1994	24/37 24/38 25/37 25/38
2000	26 November 2000 26 November 2000 19 December 2000 19 December 2000	24/37 24/38 25/37 25/38
2006	13 December 2006 13 December 2006 04 December 2006 04 December 2006	24/37 24/38 25/37 25/38
2011	08 October 2011 08 October 2011 31 October 2011 31 October 2011	24/37 24/38 25/37 25/38

of agricultural land or "other." A process was created to aid in the isolation of the well pad class from the classes for agricultural land and "other." To begin, one image was recoded to represent only the well pad class, and a second image was recoded to represent forest, agricultural land, and "other."

Since no universal size and shape exists for well pads, areas between 0.5 to 2.3 ha were used to isolate the well pads from areas that may have been misclassified as well pads. The range of 0.5–2.3 ha was used based on literature review of well pad sizes. The clump and eliminate tools available in ERDAS IMAGINE 2010 were used on the well pad only image to remove areas larger than 2.3 ha and smaller than 0.5 ha. Clump identifies contiguous pixel groups in one thematic class while eliminate removes the small clumps and replaces those clumps with the pixel value of the neighboring larger clumps. In Landsat TM imagery, the size of 2.3 ha is between 25 and 26 pixels (2.25–2.34 ha), so clumps of 25 pixels (2.25 ha) or less were eliminated. The eliminated areas were coded as background, since only the well pad class was in the image. This "clumped and eliminated" image was subtracted from original well pad classified image, which resulted in areas classified as well pads less than 2.3 ha. Clump and eliminate was then performed again on the subtracted image to remove areas less than 0.5 ha. The size of 0.5 ha falls between five and six pixels (0.45–0.54 ha) in Landsat TM imagery; therefore, clumps of five pixels (0.45 ha) or less were eliminated. This resulted in an image that contained areas between 0.5–2.3 ha classified as well pads. Areas that were initially recoded to the well pad class, but were outside the range of 0.5–2.3 ha were coded as background after this process.

The image containing areas classified as well pads between 0.5 and 2.3 ha was subtracted

Figure 2. Classified maps of the Haynesville Shale region for each year of study (1984, 1989, 1994, 2000, 2006, and 2011)



from the image containing the classes of forest, agricultural lands, and "other." The subtracted image was added back to the image of well pads between 0.5 to 2.3 ha, resulting in a classified image containing forest, agricultural land, well pad, and "other" classes.

The resulting image was masked to remove urban areas and major water bodies. Urban areas and major water bodies were removed from the images as these areas were not of specific interest to this study. Louisiana urban areas and major water bodies were downloaded from Atlas: The Louisiana Statewide GIS (http://atlas.lsu.edu, October 2011). Texas urban areas and water bodies were downloaded from the Texas Natural Resources Information System (http://www.tnris.org, October 2011). Lastly, the masked image was clumped, and clumps less than two pixels were eliminated (Figure 2).

2.6. Accuracy Assessment

Accuracy assessments were completed on all classified maps using aerial photos acquired from the United States Department of Agriculture (USDA) National Agriculture Imagery Program (NAIP) as the reference data. Although accuracy assessments were completed with aerial photos without "boots on the ground", we followed standard procedures in remote sensing when classifying a satellite image with surface features that are easily distinguishable on an aerial photograph based on their unique shape, size, and location (Campbell, 2007). A total of 300 points were randomly selected using stratified random generation with a minimum of fifty points for each class (agricultural land, forest land, and well pad). The "other" class was not included in the accuracy assessment because it largely consisted of areas that were masked (urban and water).

An error matrix was generated for each map, and contained producer's accuracy, user's accuracy, overall classification accuracy, and Kappa statistic. While no ideal classification system for land cover exists, guidelines were established to provide a basic framework for classification of remote sensing imagery, and classifications should have an accuracy level of at least 85% (Anderson et al., 1976). Therefore, 85% accuracy was the target level for accuracy for images classified in this study. Producer's accuracy is the percentage of a class correctly classified. User's accuracy represents the reliability of the classified map. Overall classification accuracy was calculated by dividing the number of correctly classified points by the number of reference points and represents the percentage of pixels classified correctly. The Kappa statistic represents the accuracy of the classified map relative to its percent accuracy above random chance assignment.

2.7. Change Detection Analysis

Post classification comparison was used for change detection analysis. Since no physical change maps, or difference images, were produced in this study change detection analysis was performed via a pixel-by-pixel analysis of each classified pixel to extract detailed from-to data to determine land cover changes. Comparisons were made on each 5-6-yr interval between scenes, and between the 1984 and 2011 scenes. For each comparison, an interactive summary matrix within ERDAS Imagine 10.1 was generated to identify the important from-to information.

2.8. Land Cover Metrics

Land cover metrics were calculated for the entire classified study area and for each of the classified categories (agricultural land, forest land, well pad, and "other"). These metrics were determined based on contiguous pixels with the same value that is defined as a patch. A minimal mapping unit of a six pixel area (0.54 ha) was used to match with the smallest size of well pad. Patches less than six pixels of size were replaced with the majority class in the surrounding area. Once each patch was identified and its area calculated, Patch-Per-Unit area (PPU) and Square Pixel (SqP) were calculated and compared for landscape fragmentation. Data used for the calculation were obtained using ERDAS IMAGINE 2010 software.

Patch-Per-Unit area was calculated using the formula shown in Equation 1 (Frohn, 1998):

$$PPU = \frac{m}{\left(n \times \lambda\right)} \tag{1}$$

where, m = the total number of patches, n = the total number of pixels in the study area, and λ is a scaling constant equal to the area of a pixel. PPU is a patch contagion index with increased PPU meaning more fragmentation.

Square pixel is an indicator for patch shape complexity as defined by Frohn (1998) calculating the area perimeter ratio using Equation 2:

$$SqP = 1 - \left(\frac{4 \times \sqrt{A}}{P}\right) \tag{2}$$

where, A = the total area of all pixels and P = the total perimeter of all pixels. Results are normalized to values between 0 and 1, with 0 indicating a square, the least complex shape (Ayad, 2005; Rutledge, 2003). For this study, an alternative form of square pixel shown as Equation 3 was used that ranges from 1 (for a square) to infinity (Frohn, 1998).

$$Sq = \left(\frac{P}{4 \times \sqrt{A}}\right) \tag{3}$$

3. RESULTS

3.1. Image Classification and Accuracy Assessment

One objective of this study was to accurately isolate well pads using Landsat TM imagery.

Results of the classified images had an overall classification accuracy range between 84.7% and 89.0% (Table 2). The 2006 classified image had the highest overall classification accuracy with 89.0%. The lowest overall classification accuracy of 84.7% was in the 2000 classified image. Each of the classified images reported similar accuracy values in the error matrices, showing consistency existed between the dates.

User's accuracy represents the reliability of the classified map. User's accuracy for forest land (96.9% to 98.7%) and agricultural land (81.8% to 88.1%) was acceptable for all classified images; however, well pad user's accuracy remained low in all classified images (50.0% to 60.0%). Images with the highest user's accuracy for well pads were the 1984, 1994, and 2006 classified images with each achieving 60.0%.

Producer's accuracy is the percentage of a class that was correctly classified. Producer's accuracy for forest land (94.6% to 97.7%), agricultural land (79.1% to 90.9%), and well pads (90.9% to 100%) remained at acceptable levels for all classified images. The well pad class had a particularly high producer's accuracy. Since the producer's accuracy of well pads was high, and the user's accuracy was low, this indicated an over classification of the number of well pads. Difficultly in isolating well pads from agricultural land and urban areas resulted in user's accuracy levels below the desired target level.

3.2. Change Detection Analysis

A summary matrix for each time series was generated with the values (hectares and percentages) representing the amount of correlation between the two images. The changes in land cover from agricultural land and forest land to well pads for the five- to six-year intervals (Table 3) showed varying degrees of change. The greatest change from agricultural land to well pads occurred between 1994 and 2000 (12,965 ha), while the conversion from forest land to well pads was found to be highest between 2006 and 2011 (5,947 ha). Between 1984 and 2011, 6,703 ha of agricultural land and 8,071 ha of forest land were converted to well pads (Table 3). The discrepancy between the amounts of agricultural land converted to well pads was likely due to classification errors, with a larger portion of the agricultural land and "other' classes being misclassified as well pads in 2000 than in the other years.

3.3. Land Cover Metrics

As expected, the results of mean patch size showed that well pads maintained the same small average size (1.1-1.2 ha) throughout the years. From 1994 to 2011, the mean patch size of forest continued to increase, while that of agriculture was decreasing. The overall mean patch size for the study area did not show a significant change over time (Figure 3).

Patch-Per-Unit area calculations showed the inverse of mean patch size. Compared with other classes, the high PPU values of well pad (85.6-94.3 per sq km) across the years indicated a much higher magnitude of fragmentation than other classes. For each year, agriculture was more fragmented than forestry. Since 1994, the two classes were heading toward two opposite directions, with agriculture becoming more fragmented (4.4, 6.8, 7.1, and 7.7 per sq km), whereas forest becoming more aggregated (1.4, 1.3, 1.0, and 0.8 per sq km) (Figure 4). The "other" class had an increasing trend of fragmentation (5.1-9.9 per sq km). PPU metrics of the entire Haynesville Shale region did not vary greatly (3.2-3.9 per sq km) over the course of the study period. The increase in overall PPU value between 2006 and 2011 (3.2-3.4 per sq km) was likely influenced by the increased natural gas exploration that began in the Haynesville Shale in 2007. The main contributor to the increase in fragmentation was found as agriculture (7.1-7.7 per sq km) and "other" (7.7-9.9 per sq km).

Square pixel indicated the shape complexity, and was greater for agriculture (240.5-292.2) than forest (145.2-199.1), well pad (112.5-184.6), and "other" (103.8-132.5) (Figure 5). Square pixel metrics can range between 1 to infinity, with higher values indicating more complexity. Well pad consistently had a lower

Table 2. Error matrices for image classifications

Reference							
	1984	Other	Forest Land	Agricultural Land	Well Pad	Total	User's Accuracy
Classified	Other	0	0	0	0	0	---
	Forest Land	4	155	1	0	160	96.9%
	Agricultural Land	5	5	77	3	90	85.6%
	Well Pad	4	0	16	30	50	60.0%
	Total	13	160	94	33		
	Producer's Accuracy	---	96.9%	81.9%	90.9%		
Overall Classification Accuracy = 87.3%, Overall Kappa statistic 0.790							
Reference							
	1989	Other	Forest Land	Agricultural Land	Well Pad	Total	User's Accuracy
Classified	Other	0	0	0	0	0	---
	Forest Land	1	165	2	0	168	98.2%
	Agricultural Land	1	8	71	2	82	86.6%
	Well Pad	6	0	15	29	50	58.0%
	Total	8	173	88	31		
	Producer's Accuracy	---	95.4%	80.7%	93.5%		
Overall Classification Accuracy = 88.3%, Overall Kappa statistic 0.799							
Reference							
	1994	Other	Forest Land	Agricultural Land	Well Pad	Total	User's Accuracy
Classified	Other	0	0	0	0	0	---
	Forest Land	1	146	1	0	148	98.6%
	Agricultural Land	5	8	88	1	102	86.3%
	Well Pad	6	0	14	30	50	60.0%
	Total	12	154	103	31		
	Producer's Accuracy	---	94.8%	85.4%	96.8%		
Overall Classification Accuracy = 88.0%, Overall Kappa statistic 0.804							
Reference							
	2000	Other	Forest Land	Agricultural Land	Well Pad	Total	User's Accuracy
Classified	Other	0	0	0	0	0	---
	Forest Land	2	157	3	0	162	96.9%
	Agricultural Land	7	9	72	0	88	81.8%
	Well Pad	9	0	16	25	50	50.0%
	Total	18	166	91	25		
	Producer's Accuracy	---	94.6%	79.1%	100%		
Overall Classification Accuracy = 84.7%, Overall Kappa statistic 0.744							

continued on following page

Table 2. Continued

Reference							
	2006	Other	Forest Land	Agricultural Land	Well Pad	Total	User's Accuracy
Classified	Other	0	0	0	0	0	---
	Forest Land	0	163	3	0	166	98.2%
	Agricultural Land	4	6	74	0	84	88.1%
	Well Pad	11	0	9	30	50	60.0%
	Total	15	169	86	30		
	Producer's Accuracy	---	96. 4%	86.0%	100%		
Overall Classification Accuracy = 89.0%, Overall Kappa statistic 0.814							
Reference							
	2011	Other	Forest Land	Agricultural Land	Well Pad	Total	User's Accuracy
Classified	Other	0	0	0	0	0	---
	Forest Land	4	166	0	0	170	97.6%
	Agricultural Land	5	4	70	1	80	87.5%
	Well Pad	15	0	7	28	50	56.0%
	Total	24	170	77	29		
	Producer's Accuracy	---	97.6%	90.9%	96.6%		
Overall Classification Accuracy = 88.0%, Overall Kappa statistic 0.798							

SqP value, which is understandable due the rectangular shape of well pads. The "other" class had an increasing trend for SqP that reached its maximum in 2011. Square pixel metrics for the entire Haynesville Shale region (277.2–346.0) showed the biggest increase between 1989 and 1994, and then continued to decrease.

4. DISCUSSION

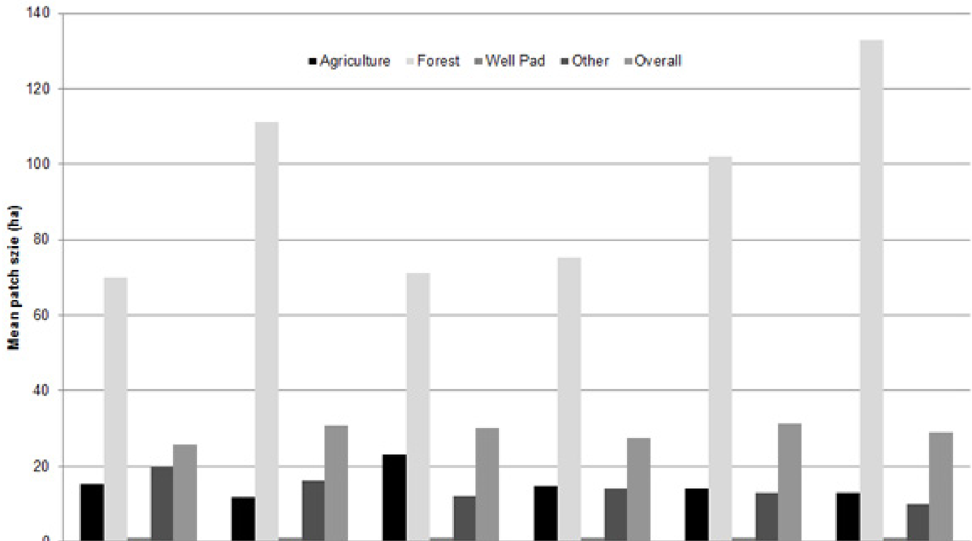
Louisiana and Texas have been greatly impacted by the recent boom in natural gas exploration and production in the Haynesville Shale region. Concern about this increase in exploration has arisen, and is partly due to the possible effects drilling has on land, including the conversion of land from forests and agricultural lands to well pads, access roads, and pipelines. This study evaluated the land area affected by well pad construction over an approximate 25-year span. During the mid-1980s oil exploration spiked in the region, and during the mid-2000s gas exploration increased.

One objective of this study was to quantify the amount of land converted from forest or agricultural land due to well pad construction over the last 25 years. To accomplish this task, images had to be classified to accurately reflect the amount of land considered well pads. Unfortunately, during identification of the classes, areas of agricultural land and man-made structures (e.g., buildings and roads) shared the same digital signature as the well pads. This led to lower user's accuracy levels in the classified maps that were used to quantify land cover changes. The accuracy of the post classification comparison is dependent on the accuracy of the initial classifications. A more consistent and highly accurate method for isolating well pads

Table 3. Land cover changes (hectares and percentages) in the Haynesville Shale region between years of study

		1984							
		Agriculture		**Forest**		**Well Pad**		**Other**	
1989	**Agriculture**	428,862	(59.5%)	90,708	(4.8%)	18,301	(61.6%)	25,557	(9.7%)
	Forest	254,260	(35.2%)	1,742,530	(92.9%)	6,691	(22.5%)	22,880	(8.6%)
	Well Pad	7,454	(1.0%)	1,444	(0.1%)	1,015	(3.4%)	1,865	(0.7%)
	Other	30,762	(4.3%)	41,359	(2.2%)	3,716	(12.5%)	214,301	(81.0%)
		1989							
		Agriculture		**Forest**		**Well Pad**		**Other**	
1994	**Agriculture**	483,750	(85.9%)	372,399	(18.4%)	9,269	(78.7%)	40,039	(13.8%)
	Forest	58,700	(10.4%)	1,606,260	(79.3%)	291	(2.5%)	42,891	(14.8%)
	Well Pad	5,320	(0.9%)	4,016	(0.2%)	1,083	(9.2%)	2,253	(0.8%)
	Other	15,658	(2.8%)	43,692	(2.1%)	1,133	(9.6%)	204,961	(70.6%)
		1994							
		Agriculture		**Forest**		**Well Pad**		**Other**	
2000	**Agriculture**	509,315	(56.3%)	145,526	(8.5%)	6,833	(53.9%)	17,558	(6.6%)
	Forest	353,914	(39.1%)	1,511,840	(88.5%)	3,337	(26.3%)	47,501	(17.9%)
	Well Pad	12,965	(1.4%)	1,912	(0.1%)	1,208	(9.6%)	1,391	(0.5%)
	Other	29,265	(3.2%)	48,862	(2.9%)	1,294	(10.2%)	198,997	(75.0%)
		2000							
		Agriculture		**Forest**		**Well Pad**		**Other**	
2006	**Agriculture**	445,630	(65.6%)	117,491	(6.1%)	12,457	(71.3%)	24,904	(8.9%)
	Forest	202,440	(29.8%)	1,745,720	(91.1%)	1,711	(9.8%)	56,214	(20.2%)
	Well Pad	4,927	(0.7%)	4,145	(0.2%)	1,297	(7.4%)	1,597	(0.6%)
	Other	26,236	(3.9%)	49,243	(2.6%)	2,011	(11.5%)	195,703	(70.3%)
		2006							
		Agriculture		**Forest**		**Well Pad**		**Other**	
2011	**Agriculture**	406,034	(67.6%)	100,666	(5.0%)	4,722	(39.4%)	24,705	(9.0%)
	Forest	156,732	(26.1%)	1,812,050	(90.3%)	1,940	(16.2%)	42,515	(15.6%)
	Well Pad	6,220	(1.1%)	5,947	(0.3%)	2,506	(21.0%)	2,126	(0.8%)
	Other	31,495	(5.2%)	87,411	(4.4%)	2,797	(23.4%)	203,838	(74.6%)
		1984							
		Agriculture		**Forest**		**Well Pad**		**Other**	
2011	**Agriculture**	359,648	(49.9%)	135,806	(7.3%)	15,219	(51.1%)	25,453	(9.6%)
	Forest	317,405	(44.0%)	1,645,890	(87.7%)	10,629	(35.8%)	39,308	(14.9%)
	Well Pad	6,703	(0.9%)	8,071	(0.4%)	789	(2.7%)	1,236	(0.4%)
	Other	37,583	(5.2%)	86,267	(4.6%)	3,086	(10.4%)	198,606	(75.1%)

Figure 3. Patch size change over time within the Haynesville Shale region



	1984	1989	1994	2000	2006	2011
Agriculture	15.4	11.6	23.0	14.8	14.1	12.9
Forest	69.9	111.4	71.1	75.4	102.0	132.8
Well Pad	1.1	1.2	1.1	1.1	1.1	1.1
Other	19.7	16.1	12.2	14.2	12.9	10.2
Overall	25.6	30.9	30.3	27.4	31.2	29.0

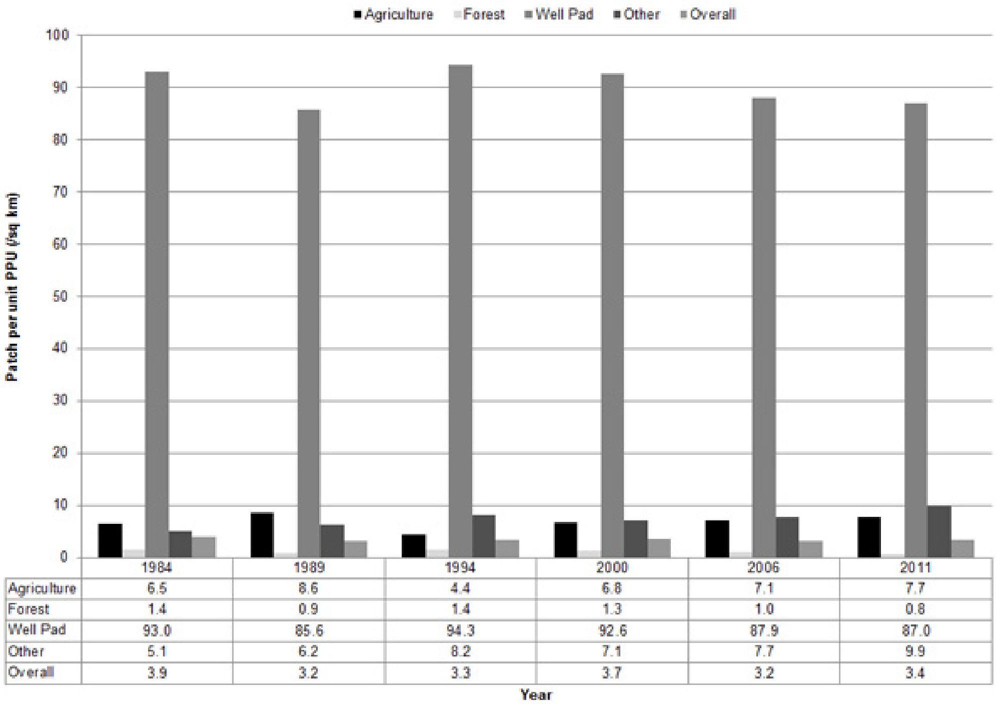
in Landsat TM imagery needs to be developed for creation of reliable thematic maps.

Object-based classification has produced results indicating it may be more accurate than pixel-based classification (Dorren et al., 2003; Matinfar et al., 2007). The use of a combination of pixel-based and object-based classification has also shown promising results in classification accuracy improvement (Aguirre-Gutiérrez et al., 2010). Additionally, high resolution aerial photos may provide more accurate analysis of well pads. However, this may only be practical when dealing with smaller areas within the Haynesville Shale rather than the entire region. An object-based method combining Landsat TM data and aerial photos has also improved classification accuracy (Geneletti & Gorte, 2003).

Satellite images acquired for this study were taken during winter months. Due to the large study area and the need for cloud free images, winter months had more available imagery than summer months. However, summer images may have been better to use for classification of well pads because agricultural land and well pads are more likely to have the same digital signature in winter months than summer months. During summer months, more areas of agricultural land would be growing crops or grasses that would have a different digital signature than the cleared land around well pads.

Change detection analysis for the Haynesville Shale region showed a change in both forest and agricultural lands due to well pads. When each approximate five-year interval was examined, results indicated a greater percent change in agricultural land than forest land to well pads. One consideration when examining results was to realize that confusion existed between the classification of agricultural land and well pads; however, little error existed when classifying forest land. Due to this, more discrepancies may exist in the change detection analysis of agricultural land than forest land.

Figure 4. Patch contagion change over time within the Haynesville Shale region



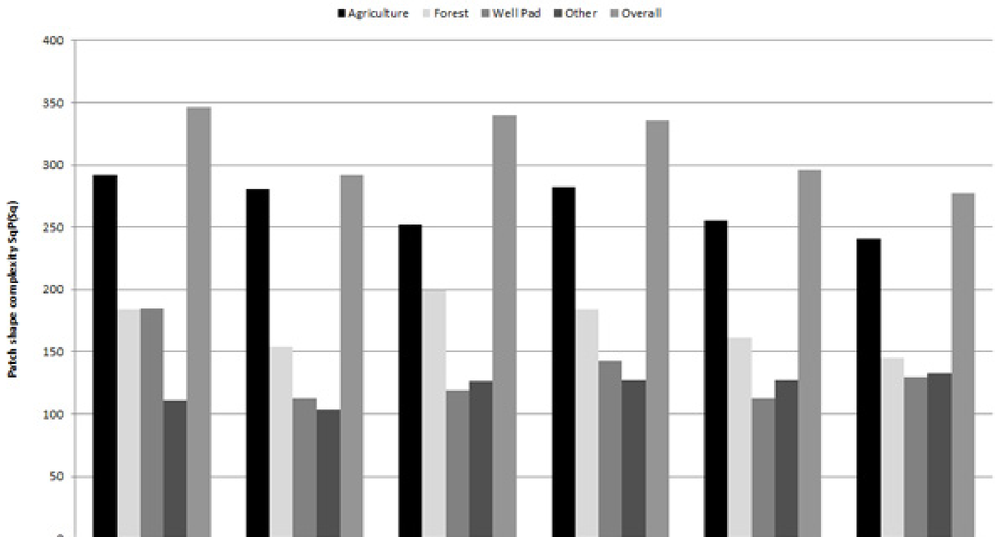
	1984	1989	1994	2000	2006	2011
Agriculture	6.5	8.6	4.4	6.8	7.1	7.7
Forest	1.4	0.9	1.4	1.3	1.0	0.8
Well Pad	93.0	85.6	94.3	92.6	87.9	87.0
Other	5.1	6.2	8.2	7.1	7.7	9.9
Overall	3.9	3.2	3.3	3.7	3.2	3.4

Results for the overall time period (1984–2011) indicated more forest land changed to well pad (8,071 ha) than agricultural land to well pad (6,703 ha). Forest land covered more of the study area than agricultural land, so placement of well pads was more likely to occur on forest land than agricultural land. Additionally, between 1984 and 2011 a large amount of agricultural land was converted to forest (317,405 ha). The increase in agricultural land converted to forest was also observed by Hung et al. (2004) within this region.

Patch-Per-Unit area and Square Pixel were used to analyze fragmentation and complexity of patches within the Haynesville Shale. Patch-Per-Unit area trends reported in this study were similar to those reported by Hung et al. (2004) for an East Texas area that falls within the Haynesville Shale region. Following 1994, agricultural lands showed an increased trend in fragmentation. Forest lands had an opposite trend, with a decrease in fragmentation after 1994 (Figure 3). Although well pad showed much higher magnitudes of fragmentation, its contribution to the overall landscape was not significant as it only accounted for a small portion of the study area. Notably, the "other" class had increasing fragmentation over the time period examined that was likely due to new roads and construction of other man-made structures.

Overall, the Haynesville Shale region experienced an increasing trend in fragmentation with the greatest increase occurring between 2006 and 2011. During this period, the two major contributors were agriculture and "other". More well pads were constructed in agricultural lands due to easy access. The "other" class included roads and pipelines, which increased in number as natural gas exploration increased. While roads and pipelines were difficult to discern using Landsat imagery, some areas were identified and were classified as "other" in this study. These areas likely account for the increased fragmentation that occurred between 2006 and

Figure 5. Patch shape complexity change over time within the Haynesville Shale region



	1984	1989	1994	2000	2006	2011
Agriculture	292.2	280.7	252.2	282.0	255.5	240.5
Forest	184.2	153.7	199.1	183.7	161.5	145.2
Well Pad	184.6	112.5	119.3	142.8	112.7	129.5
Other	111.4	103.8	126.7	126.9	127.0	132.5
Overall	346.0	292.0	340.0	336.0	296.4	277.2

Year

2011, indicating that the natural gas exploration that began in 2007 in the Haynesville Shale increased landscape fragmentation.

The SqP values depicted the patch shape complexity. Agricultural lands decreased in shape complexity between 1984 and 1994, but increased between 1994 and 2000. Following 2000, agricultural lands showed a decreasing trend in shape complexity, even though it was experiencing higher fragmentation. Forest lands showed a decrease in shape complexity following 1994. Between agriculture and forest, agriculture had a consistently higher shape complexity value than forest, suggesting that agriculture was practiced in smaller areas with more irregular shapes, whereas forests were grown in much larger areas. Although well pads were small in size, they remained less complex in shape than agriculture and forest due the nature of its rectangular shape. The "other" class did display an increasing SqP trend from 1984 to 2011. It reached its maximum (132.5) in 2011 suggesting that the natural gas exploration beginning 2007 in the Haynesville Shale had an impact on the landscape patch shape complexity caused by the construction such as access roads. This highest shape complexity for the "other" class in 2011 echoed the fact that the highest fragmentation for this class was found in 2011 as well. The "other" class included any land cover that was not classified as agriculture, forest, or well. It could be bare land, road, and any other man-made structure that had the highest impact to the landscape other than well pad itself.

Landscape metrics were calculated using the classified maps generated for this study. The fidelity of these measures relies on the accuracy of the classified maps. Furthermore, the image processes such as clump and eliminate could also introduce errors that propagate to the landscape metrics, While they report fragmentation and high levels of complexity within the shale region, further analysis using higher user's accuracy on well pad classification may provide a better understanding of landscape dynamics involving forest land, agricultural land, and well pad in the Haynesville Shale region.

5. CONCLUSION

Landsat imagery had lower user's accuracy for identification of well pads than expected. While the overall accuracy of each classified map was above the 85% target level, the user's accuracy of well pad identification (50.0%–60.0%) was too low to obtain highly reliable measurements for change detection analysis and land cover metrics.

A summary matrix of from-to data for all forest land, agricultural land, and well pads was generated to quantify the amount of change every 5–6 years and the overall time period (1984–2011). The total amount of land cover that changed in the Haynesville Shale region from 1984 to 2011 was 686,766 ha, which resulted in a total land cover change of 24%. The findings showed an overall change of forest and agricultural land to well pads to be 0.1% (8,071 ha of forest and 6,703 ha of agricultural land).

Landscape metrics were used to determine surface disturbance to forest and agricultural lands due to well pads. The results showed that agriculture was more fragmented and more complex in shape than forest at all times. From 1994 to 2011, agriculture became more fragmented, while forest became more aggregated. In 2011, the "other" class reached its highest magnitude both in fragmentation and shape complexity that might be related to the construction of well pads as well as other developments. Overall, oil and gas exploration within the Haynesville Shale region had disturbed forest and agricultural lands. It should be noted that access roads were not included in this study, so the impact of petroleum exploration and production in this study area are likely higher than values reported as what was found in the landscape metrics for the "other" class. Further research using higher spatial resolution data sets like QuickBird or GeoEye may produce a higher user's classification accuracy and report more detailed analysis of changes in the landscape.

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Daniel Unger is currently a Professor of Geospatial Science within the Arthur Temple College of Forestry and Agriculture at Stephen F. Austin State University. Previously he was an Assistant Professor of Natural Resource Measurements within the Department of Forestry at Southern Illinois University. His academic interests include quantifying and qualifying natural resources using remote sensing, geographic information systems, and global positioning systems technology. He received a BSF in Forest Management from Purdue University; BS in General Business from Purdue University; MS in Forest Biometrics from The Pennsylvania State University; PhD in Remote Sensing and GIS from the University of Idaho.

I-Kuai Hung is an Associate Professor in the Arthur Temple College of Forestry and Agriculture at Stephen F. Austin State University in Nacogdoches, Texas. Previously he was a forester with the Experimental Forest of Taiwan University in Taiwan. He teaches GIS and spatial analysis courses with a focus on applications in natural resource management. His research interest ranges from forest inventory, landscape ecology, recreation planning to remote sensing. His most recent projects include lidar remote sensing to derive forest measurements, sub-pixel and feature based land cover classification, and Web GIS for botanical gardens. He received his BS and MS, both in Forestry, from Taiwan University; PhD in Forestry from Stephen F. Austin State University.

Kenneth Farrish is currently the Director of the Division of Environmental Science and Arnold Distinguished Professor in the Arthur Temple College of Forestry and Agriculture at Stephen F. Austin State University. His research interests include soil science, remediation of contaminated soils, and water resources. Farrish teaches courses in soil science and remediation and reclamation of disturbed lands. He received the BS and MS degrees from Michigan Technological University, and the PhD from the University of Minnesota.

Darinda Dans was previously a Research Associate at the Waters of East Texas Center, Division of Environmental Science, Arthur Temple College of Forestry and Agriculture, Stephen F. Austin State University and a Research Associate at the Red River Research Station with the Louisiana State University Agricultural Center. She received a BS in Environmental Management Systems from Louisiana State University and a MS in Environmental Science from Stephen F. Austin State University. Her research interests include water resource issues and management, wetland science, and geographic information systems.