A Comparison of Coincident Landsat-5 TM and Resourcesat-1 AWiFS Imagery for Classifying Croplands

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Abstract

A comparison of land-cover maps, emphasizing row crop agriculture, resulting from independent classifications of coincident Landsat-5 Thematic Mapper (TM) and Resourcesat-1 Advanced Wide Field Sensor (AWiFS) imagery is presented. Three agriculturally intensive study areas within the midsection of the United States were analyzed during the peak of their growing season. For each region the data were collected within the same hour during August 2005. Identical decision tree style classification methodologies relying on ground truth from the June Agricultural Survey were applied to the image pairs for each of the three cases. The direct comparison of mapping accuracy results show, on average, the TM output to perform slightly better than that of the complimentary AWIFS. It is concluded AWIFS is a valid alternative to TM for classifying cultivated agriculture in areas with reasonably large field sizes. Furthermore, AWIFS offers increased benefits due to larger swath widths and shorter revisit frequencies.

Introduction

The mission of the National Agricultural Statistics Service (NASS) is to providing timely, accurate, and useful statistics in service to United States agriculture. To meet the goal, NASS implements hundreds of annual surveys, plus a comprehensive census every five years, which continually compile and tabulate information on domestic crops and livestock. Demographic, environmental, and economic data related to agriculture is also gathered. The information is collected by a variety of methods including mail, phone, Internet, or personal interview.

The flagship survey effort within NASS is the June Agricultural Survey (JAS). Annually, enumerators visit over 11,000 sample sites, encompassing roughly 85,000 land tracks, distributed across the U.S. Data is collected on planted crop acreage, livestock inventories, and farm economics. Each site is usually one square mile in size and location determined from a stratified random sample selected from a probability-based area frame. The samples are primarily drawn from agriculturally intensive regions and amount to a ground sampling rate of one half percent or denser in those areas. The data from all of the visited sites is ultimately aggregated to state and national levels and used to make agricultural planted acreage estimates for the current year.

The need often arises for the June collected statistical information to be compiled at a geographically finer level than what the JAS can provide. Remotely sensed imagery used in conjunction with concurrent JAS land-use data presents a means for identifying the spatial distribution of crops down to the level of individual fields. This is employed through a "supervised" image classification methodology and is made robust because of the geographically and randomly distributed nature of the JAS. Thus, for several years NASS has leveraged the JAS ground truth information and produced categorized land-cover image products, known as Cropland Data Layers (CDL) (Craig, 2001; Mueller, 2000). Focus for the CDL program has been on select central and southern U.S. states dominated by intensive agriculture and has grown in scope since inception during the late-1990s.

The CDL products have a variety of applications, especially when integrated into a geographic information system (GIS). Primary benefits within NASS include the ability to tighten confidence intervals for the state level acreage estimates derived from the JAS, derivation of county level acreage estimates, and feedback for the defining and updating of the land-use strata for which the JAS is based. Beyond NASS, examples of known uses include assessing regional scale environmental impacts from farming, detection of land-use changes in agricultural fringe areas, validation of crop classifications derived from coarser-scaled imagery, and time series analysis of cropping patterns. Additionally, since the CDLs are tailored to cropland mapping, the information from it can also be used to supplement other land-cover mapping efforts which in themselves may lack sufficient detail in agricultural classes.

Landsat-5 and -7 have been the primary source of the remotely sensed data for the CDL program (Craig, 2002). Reasons for utilizing Landsat data include its appropriate pixel size and spectral bands for mapping agricultural cover types, sufficient revisit rate usually allowing for one or more cloud-free image acquisitions during ideal times of the growing season, cost effectiveness, and operational nature. Furthermore, land-cover mapping applications with Landsat are common given a large user community (USDOI, 2006). There is a particularly large following specifically for monitoring agriculture and natural resources. Within the U.S. Department of Agriculture (USDA) Landsat imagery is analyzed

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by the Foreign Agricultural Service, Natural Resources Conservation Service, Forest Service, Farm Service Agency, and Risk Management Agency, in addition to NASS.

However, with the uncertainly of the Landsat program due to limited remaining lifespan expectancy with the greater than 20-year age of the Landsat-5 TM platform, degradation of the Enhanced Thematic Mapper Plus (ETM+) sensor because of the Scan Line Corrector (SLC) failure in 2003 aboard Landsat-7, and doubts about the likeliness and timeliness of follow on missions, NASS began exploring other data sources. The most appropriate and Landsat-like imagery to be found was that from the Indian Remote Sensing's (IRS) Resourcesat-1 AWIFS. Appealing characteristics included a large swath width, inclusion of spectral bands important to crop identification and monitoring, and cost effectiveness per unit area. Additionally, the geographically wide images had the added benefit of creating large overlap areas between adjacent scenes which in effect shortened revisit times.

In 2004, NASS tasked the Resourcesat AWIFS sensor to collect data over much of the upper and lower Mississippi River basin during the month of August. About 150 scenes were obtained with a general objective to assess the quality and timeliness of the data. A more targeted goal was to evaluate the suitability of the data to build a CDL and test the acreage estimate accuracy. Quantitative assessment of the 2004 data's utility within the CDL program was limited, but AWIFS was thought to be promising as a compromise because derived classifications and acreage estimates for major crops were comparable (Boryan and Craig, 2005). Minimally, AWIFS satisfied the goal of providing supplemental information in regions where a high-quality Landsat scene was not available due to cloud cover.

The next year NASS committed further to collecting AWIFS imagery to better explore and document its utility. Again, data was collected for the central and southern portions of the U.S. Data collection times coincided with late spring and middle summer of 2005. More detailed comparative assessments were undertaken and further boosted the notion that Resourcesat-1 could be a suitable alternative to Landsat for crop type mapping. Still lacking however was a direct quantitative comparison of coincident, in date and location, imagery which would in effect control for differences in classifications that could otherwise arise from changes in atmospheric and ground conditions.

Even outside of NASS, very little known research has been published to assess the utility of AWIFS data, whether for agricultural applications or disciplines beyond. Reasons may be varied, but likely a result of the newness, limited availability, unfamiliarity, degraded imagery specification compared to Landsat TM and ETM+, or competition from other sensors such as SPOT or ASTER. Of note however, are publications from Kiran-Chand *et al.* (2006) who utilized AWIFS imagery in conjunction with MODIS to validate a Defense Metrological Satellite Program fire detection product over India, and from Kulkarni *et al.* (2006) who applied AWIFS data for snow cover monitoring in the Himalayas.

Thus, the goal of this study is straightforward: to quantitatively assess the utility of AWIFS imagery for land-cover mapping, specifically targeting crop type identification, and determine whether AWIFS is a valid replacement data source for Landsat. TM data will be used as a benchmark from which to compare AWIFS, because TM has been used nearly exclusively for the NASS CDL program since the SLC problem arose on the ETM+ sensor. Furthermore, TM is currently considered the *de facto* data source in much of the land-cover monitoring community.

Background

The Resourcesat-1 (IRS-P6) satellite imaging system is a relative newcomer as a source for spaceborne remotely sensed imagery. The platform was launched in 2003 and follows a long lineage of IRS land imaging satellites dating back to 1988. Resourcesat-1 represents increased capabilities over previous generation IRS satellites and carries three imaging instruments with complimentary characteristics (NRSA, 2003; Lutes, 2005). The sensor with the broadest areal coverage is AWIFS. It has a nadir ground sample distance (GSD) of 56 m and a swath width of 740 km. The wide field-of-view imaging is accomplished by two separate but identical AWIFS multispectral cameras which are oppositely titled approximately 12 degrees with respect to nadir with scenes that overlap by 8.4 km. They each contain a linear charge coupled device (CCD) array utilizing 6,000 pixels capturing data in four spectral bands (green, red, near-infrared, and shortwave-infrared).

The other two Resourcesat-1 sensors are the high resolution Linear Imaging Self-Scanner (LISS-IV) which has a GSD of 5.8 m and the medium resolution Linear Imaging Self Scanner (LISS-III) with a GSD of 23.5 m. LISS-III's CCDs are identical to those of AWIFS and collect data in parallel. This setup affords the ability to create a higher resolution reference set of data within the middle of the AWIFS strip. LISS-IV is more specialized and can collect imagery 4,000 pixels wide in multispectral mode (green, red, and near-infrared) or 12,000 pixels wide in mono mode (normally the red band). NASS has not studied the utility of LISS-III or LISS-IV specifically for regional scale mapping of agriculture partially due to their limited swath widths, 141.0 and 23.9 km, respectively, and in the case of LISS-III, temporal repeat coverage of only 24 days. LISS-IV, however, can be pointed up to 26 degrees from nadir to improve revisit times to only five days over limited areas.

Specifics about Landsat-5 TM and Resourcesat-1 AWIFS are highlighted in Table 1. Notable similarities of the sensors are the overlap of green, red, near-infrared (NIR), and shortwave-infrared (SWIR) spectral bands. Not only are the spectral ranges for each nearly identical, but the AWIFS designers went as far as labeling the bands to correspond to those of TM. Overpass times are also similar, with Resourcesat-1 lagging Landsat-5 by

Table 1. Sensor Specifications

	Landsat-5 TM	Resourcesat-1 AWIFS
Launch	01 March 1984	17 October 2003
Altitude	705 km	817 km
Orbit	circular, sun-synchronous	circular, sun-synchronous
Inclination	98.2°	98.7°
Period	99 minutes	101 minutes
Equatorial crossing	9:45 AM ± 15 minutes	10:30 AM ± 5 minutes
Revisit rate	16 days	24 days
Pixel size	30 m (reflective)	56 m
	120 m (thermal)	—
Quantization:	8-bit	10-bit
Spectral bands	1: Blue (0.45–0.52 μm)	—
	2: Green (0.52–0.60 μm)	2: Green (0.52–0.59 μm)
	3: Red (0.63–0.69 μm)	3: Red (0.62–0.68 μm)
	4: NIR (0.76–0.90 μm)	4: NIR (0.77–0.86 μm)
	5: SWIR (1.55–1.75 μm)	5: SWIR
	6: Thermal (10.40–12.50 μm)	— (1.55–1.70 μm)
	7: MIR (2.08–2.35 μm)	—
Field of view	14.7°	42.1°
Swath width	185 km	737 km
Scene size	184 × 185.2 km	370 × 370 km

about 45 minutes. A key dissimilarity between the sensors is the exclusion of the blue, mid-infrared (MIR), and thermal-infrared channels on AWIFS. Also, an important difference is the sampled ground size of the pixels. AWIFS's pixels are 56 m squared versus 30 for TM. As a result, AWIFS pixels are approximately 3.5 times larger in area than TM pixels. The swath width of AWIFS is about four times wider than TM, but because of the bigger pixel sizes, the overall numbers of pixels per scene are comparable. AWIFS has a large field of view so the native area of the pixels increases to approximately 70 m resolution at off-nadir scene edges. At these edges the resulting view angle is over 20 degrees from nadir. TM's maximum off-nadir viewing angle is only about seven degrees so native pixel size increase on the scene edges is minimal. From the specifications in the table alone, one might conclude AWIFS has less ability to acquire repeat scenes over the same location since it takes 24 days versus 16 to duplicate its orbital path. However, because AWIFS has very wide footprints, the side overlays create repeat frequencies for a given area every five days. Additionally, 80 percent of a path is overlapped by a successive orbit, and as a result, it is common to get even greater repeat coverage for smaller geographic areas. In some cases, overlap occurs the very next day.

Study Area

In order to directly assess cropland map classification outcomes of TM versus AWIFS data, coincident scenes, in both time and location, were deemed most desirable. Images collected at the same time control for differences that often arise from changed atmospheric (e.g., haze, humidity) or ground conditions (e.g., plant phenology, soil moisture) which could alter otherwise similar classification efforts. By chance, coincident data collects occurred several times during the summer of 2005 within the midsection of the U.S. Three scene intersections were chosen as best and further utilized for evaluating cropland detection between sensors. Factors in selecting the test imagery were based on their location residing in an agriculturally dominant setting, proper timing for crop phenology, minimal amounts of clouds and haze, and sufficient overlap area between scenes. Additionally, given the large variation of view angle and GSD across track with AWIFS and two overlapping imaging sensors, it was also seen desirable to include different combinations of view angle and test both AWIFS cameras when possible.

The first example presented was based on imagery collected 20 August 2005. Geographically, the data resided over a section of the agriculturally intensive Mississippi River Alluvial Plain, locally known as the Delta, centered over the eastern portion of the state of Arkansas (Figure 1). A small portion of the study site extended south into Louisiana, and to a lesser extent, north into Missouri. The majority of the data was in Arkansas though and thus how referred to here for discussion. The Arkansas imagery originally spanned west of the Delta region, but that portion was excluded from analysis because the region is almost exclusively non-cropland in nature, and thus little ground truth data was collected. Based on the 2005 JAS statistics, about two-thirds of the land in this Arkansas study area was dedicated to field crop agriculture dominated by soybeans, rice, and cotton (Table 2). Corn was also found, but in lesser amounts. During mid-August, the time for which the data were collected, soybeans and cotton were in the middle of their growing season while rice and corn were nearing harvest (USDA, 1997). Scene quality was very good with only a few cumulous clouds present along the south and western edges of the study area. Because the images were collected within an hour of one another, the clouds had only shifted slightly between scenes. The Resourcesat-1 data were along the mid-scene of the west-sided AWIFS camera, and thus represented pixel reflectances oriented away from the sun at an angle averaging roughly ten degrees from nadir (Table 3). Oppositely, the corresponding Landsat-5 TM data angled slightly into the sun, albeit only about five degrees on average, because of its location along the eastern edge of its scene.

The second study area was found in south-central Iowa. It was the smallest geographically of the three examples. The overlap area originally extended south into Missouri but was excluded because of little training data and cloud issues in that region. The data for Iowa were captured on 18 August 2005, two days prior to the Arkansas example. In terms of agriculture, this region was predominately made up of corn and soybean row cropping, particularly toward the northern extent. These crops were in the midst of their growing season during mid-August. There was also a sizable amount of land, particularly toward the south, dedicated to forage like alfalfa, hay, and pasture. Non-agriculture cover types were a mix of urban and woodland. The city of Des Moines was nearly centered vertically within the resulting strip of coincident data. A few cumulous clouds appeared in the scenes concentrated along the northern extent, but otherwise the data was of high quality. The AWIFS imagery was from Resourcesat-1's eastward facing camera and represented the greatest off-nadir viewing angle possible, trending toward the sun by about 20 degrees. The result was a native ground sample distance of approximately 70 m. In contrast, the reflectances from the TM data were oriented away from the sun, given the area of interest fell onto its western scene edge. Also, the TM viewing angle was much less extreme because of its narrower field of view. The Iowa example presented a scenario with the most opposed viewing geometry possible between the AWIFS and TM data.

The final case of coincident data was from northeastern Illinois and collected on 29 August 2005. In terms of geographic area, the Illinois site was about twice as large as the Arkansas study case and four times that of Iowa. Corn and soybeans were the majority crop cover type, as was in Iowa. A portion of the Chicago metropolitan area was found in the northeastern section and accounted for about ten percent of the land-cover over the examined region. The late-August date was still well within the heart of the growing season and appropriate for cropland mapping. Cumulous clouds were present toward the northern edge of the area along with a thick cirrus band in the extreme southeast. The AWIFS imagery was from the eastern Resourcesat-1 camera centered along the scene's midsection and thus presented an example of moderate view angle toward the sun. The TM swath was used almost in entirety, so the average pixel view angle was near zero with an equal number of pixels oriented toward the sun as away.

Methodology

A classification tree analysis (CTA) methodology (Friedl and Brodley, 1997, Lawrence and Wright, 2001) was used to perform identical but independent classifications on the three coincident image pairs. Leica Geosystems ERDAS Imagine® 9.0 was used for imagery preparation, NASS PEDITOR software for digitization and attribution of the NASS JAS enumerated field boundaries, ESRI ArcGIS® 9.1 for further analysis and management of those polygons, and See®5.0 2.0 for derivation of the decision tree classification rules (Quinlan, 1993). The Imagine® "NLCD Mapping Tool" extension provided by the U.S. Geological Survey (USGS) (Homer *et al.*, 2004) was used to more easily interface See®5.0 with Imagine's tools.

The first step consisted of compiling for each of the study areas the intersecting 2005 JAS data. In raw form, the

Figure 1. Study area locations.

TABLE 2. DOMINANT COVER TYPES AND ESTIMATED AREA DERIVED FROM 2005 NASS JAS

Arkansas		Iowa		Illinois	
Cover Type	Area %	Cover type	Area %	Cover type	Area %
Corn	3	Alfalfa	7	Alfalfa	2
Cotton	10	Corn	28	Corn	45
Rice	24	Soybeans	20	Soybeans	32
Soybeans	32	Idle cropland	9	Other cropland	2
Idle cropland	3	Pasture/Hay	16	Idle cropland	1
Pasture/Hay	7	Non-agricultural	20	Pasture/Hay	3
Woodland	14		100	Woodland	4
Developed	4			Developed	11
Water	3				100
	100				

Table 3. Scene Geometries

	Arkansas	Iowa	Illinois
Scene area (ha)	2,578,086	1,240,869	5,597,249
Average view angle			
TM	+5°	−7°	0°
AWiFS	−10°	+20°	+10°
AWiFS camera	west	east	east
Average AWiFS GSD (m)	60	70	60

annual JAS instrument consists of 24-inch by 24-inch paper-based maps with an accompanying questionnaire containing attribute information. The map component contains the boundary of a one square mile area sample unit known internally to NASS as a "segment." Recent aerial photography is depicted in the background for reference and scaled at 1:8 000. The questionnaire contains, among other things, a list of possible land-cover types and a place to record estimated acreage for each. Explaining the breadth of the JAS further, each segment is randomly selected from a NASS-defined area frame of contiguous segments spanning the entire U.S. To improve the efficiency of the sampling, the segments are stratified into a few categories based on the percentage of the land-cover dedicated to agriculture. Thus, minimally intensive agricultural regions are sampled less frequently than those from highly intensive areas. For example, in 2005 the state of Iowa, which has a very high percentage of land dedicated to agriculture, had 452 area segments chosen for the JAS. Arid Nevada on the other hand, had only 26 segments, even though the total land area is twice the size. In terms of the total amount of land area sampled, the Iowa study subset area had approximately three-fourths of one percent JAS coverage. The Illinois study area had a similar sampling frequency. More intense though was the Arkansas Delta region which had nearly two percent of the land area sampled.

During the first two weeks of June, trained enumerators visit each segment and delineate by colored pencil onto the survey map the current land-cover boundaries. Alongside, the questionnaire is completed describing what cover type was found within each of the defined homogeneous areas. The information is determined visually and by interviewing someone responsible with the land management at that location. The NASS survey process places more emphasis and detail on discriminating agricultural cover types, particularly cropland, versus those of non-agriculture classes. Thus, while differentiation between crop types is always expected within the data, no effort is made to place non-agricultural classes into more than just simple categories such as "urban," "woodland," and "water." Furthermore; in some cases an enumerator may simply lumped anything not agriculture into a single class, "non-agricultural."

The land track boundary information is not archived digitally, since NASS only needs the tabular information to produce its state and nation-wide estimates of planted acreage for the U.S. crop commodities. So next, the 2005 JAS field boundaries from the paper maps were "heads-up" digitized into a GIS for use as ground truth polygons. Same season map projected Landsat TM images were used for spatial referencing of the field boundaries within the GIS. Topology was checked to assure no gaps or overlaps existed between adjacent land-cover units within a segment. Linked to each polygon was the attribute information about cover type and estimated acreage recorded from the corresponding JAS questionnaire. The reported acreage value was compared against the drawn acreage to improve confidence the field were properly delineated. If a large discrepancy was found, then the polygon was flagged as bad and ignored for later use. In total, the Arkansas study region contained 199 segments, Iowa 38, and Illinois 163. Respectively, they contained 1,793, 563, and 3,648 homogenous cover type polygons.

Next, the land tract level polygons were refined. Each - digitized field was manually inspected to see if it intersected a cloud top or shadow in either the coincident TM or AWIFS imagery, and if so, discarded from any further analysis. Also eliminated from the ground truth polygons were double-cropped fields (those with more than one planting per year) since only single date summer imagery was being used in the comparison. Furthermore, only majority cover type categories were utilized since often there were not enough samples from minority ones to be reasonably depicted across the scene. This involved combining smaller classes into more generalized ones and occurred more commonly for non-cropland categories. For example, in Iowa, all non-agriculture classes were collapsed together because there were deemed too few samples of urban, woodland, and water to be representative alone.

With the complete GIS of the JAS in place, the polygons for each of the three study cases were randomly sampled by record and divided into two sets of equal length. One set of the JAS polygons were tasked for training the image classifier and the other placed aside for validation of the output later. The training-set half of the polygons were further refined. To create spectrally pure ground truth training signatures, the polygons were buffered inward by a distance of 50 m. The distance was chosen as compromise between being sufficiently large enough to rid spectrally mixed edge pixels in either the 30 m TM and 56 m AWIFS data, yet not so large as to completely eliminate training polygons from fields that were small to begin with. Finally, the buffered training polygons were rasterized to a 15 m grid, assuring increased spatial precision beyond either imagery dataset, from which to draw training samples used for the CTA.

The Arkansas study area analysis was performed in the USGS-defined Continental U.S. Albers Equal Area projection. The Iowa dataset was analyzed in Universal Transverse Mercator, Zone 15 north, and the Illinois dataset in Zone 16. All reprojections were done using a cubic convolution resampling with the output grid preserved to the original pixel size of 30 m for TM and 56 m for AWIFS. The JAS vector information was map projected to the same extents as the corresponding satellite imagery before being converted to raster form.

Classification of the raw imagery was performed first using the JAS data in conjunction with the TM and then with the AWIFS data for each case. All bands of data were used as input other than TM's thermal (band 6) due to its coarse spatial resolution of only 120 m. The TM imagery was analyzed in its native 8-bit color depth. AWIFS was also analyzed in 8-bit, but after having been linearly rescaled from the native 10-bit. Random point samples, at a rate of 10 percent of the total, were drawn from within the training pixels and used to derive the decision trees. See®5.0's boosting (Quinlan, 1996) option was set to 10 trials and global pruning at 25 percent. Analysis was performed on a per pixel basis and thus no neighboring contextual information added.

Finally, output from each classification was assessed against the fifty percent of JAS data that was withheld for validation. The validation polygon data was not buffered, unlike with the training data, but were again rasterized to 15 m preserving a reasonable amount of edge detail. For each of the cases the classified image was then intersected with the validation data to produce an error matrix defining how the predicted classification faired against the ground truth (Congalton and Green, 1999).

Results

Overall map accuracy and Kappa statistics are presented in Table 4. Comparative statistics were similar for each study area. For Iowa, the classification scenario resulted more favorably to the AWiFS analysis. Overall accuracies were 59.1 percent for TM and 61.6 percent for AWIFS, a difference of 2.5. Also, similarly trending were the Kappas with TM yielding 0.491 and AWIFS 0.520, a difference of 0.029. Within the Arkansas focus region, the overall accuracies and Kappas were greater than for Iowa. Results from Landsat's sensor showed a modest edge over Resourcesat's with a 1.0 accuracy difference (69.4 percent versus 68.4 percent, respectively) and a Kappa difference of 0.014 (0.590 versus 0.576). Finally, the best results overall came from the Illinois subset utilizing TM which showed an even larger mapping performance gap over AWIFS. TM was a whole five percentage points better than AWIFS in map accuracy (75.8 percent versus 70.8 percent) and 0.082 for the Kappa statistic (0.612 versus 0.530). Of note, across the study areas the TM Kappa was better in Illinois than for Arkansas, but the reverse was found for AWIFS. Taking a general average of accuracy and Kappa differences between the three study cases implies classifications from TM outperformed AWIFS, albeit modestly. All differences were found to be statistically significant at the pixel level.

Table 5 breaks out the accuracies by major cover types to provide a more detailed look at how the classifications performed. Within Table 5a, the values represent the producer's accuracies, or how well the general classification predicted within the validation areas. Expressed inversely, subtracting the producer's accuracy from 1.0 gives the omission error. Equally important, Table 5b shows the user's accuracies. The inverse of the user's accuracy is the commission error. For most classes across sensors the producer's and user's accuracies were similar and within class trends tended to mimic those of the overall statistics. In general, the dominant classes related to the major crop types performed the best. Soybeans, corn, rice, and cotton categorized more easily than non-cropland classes. Herbaceous cover types like alfalfa and pasture/hay struggled to give even marginal results. Idle cropland accuracies were even worse on average. Overall, the non-agricultural classes performed relatively poorly while row crop classes did the best.

Subset examples of the final output maps are shown in Plate 1 to provide a geographical perspective of the classification differences. In general, all three examples showed similar patterns, especially at the agricultural field level, and thus reinforced the tabular results from Tables 4 and 5. Major differences within the dominant crop cover types of corn, soybeans, and rice were difficult to find. However, transitions between land-cover boundaries were more sharply defined in the TM maps and non-agricultural classes appeared more reasonable. For example, in Iowa's TM classification there was better definition of roads (classed as non-agricultural) and no suggestion of pasture/hay incorrectly classified within the urban region. Additionally, the overall percentage of "speckling" was about the same for all classifications but more noticeable within AWIFS when viewed at the same scale as TM.

As noted earlier, the main discrepancy in the sensors' design comes from the lack of blue (band 1) and MIR (band 7) reflectance channels and the decreased pixels resolution of 56 m on AWIFS. More insight could be gained on the relative importance of each by altering the TM data to meet the same specifications as AWIFS. Thus, three more classifications were performed on each study area. First, the TM data were analyzed without bands 1 and 7, but keeping with the original spatial resolution of 30 m. Next, all six TM bands were used in the analysis, but after degrading them to the 56 m resolution using cubic convolution resampling. And finally, the TM data was both stripped of bands 1 and 7 and resampled to 56 m, thus matching the characteristics of AWIFS. Each of the new data sources was reclassified with the same methodology as before and accuracies computed.

Results for each test are presented in Table 6. The original TM and AWIFS classification numbers are shown again for direct reference. The accuracies and Kappas were reduced at all three study sites with the degradation of the TM data, and in some cases the differences were more pronounced than for others. In Iowa for starters, very little change occurred. The withholding of the blue and MIR bands only created a 0.2 point difference drop in accuracy percentage and 0.003 in Kappa. Spatial degradation to the 56 m resampling effort impacted the results more with a drop of 0.9 in accuracy and 0.012 in Kappa. The impact of the combined band removal and pixel resampling was 56.6 percent, or five percentage points below the raw numbers for the AWIFS classification. If all else were equal, it may have been expected for the accuracies of the degraded TM data to improve and match that of the true AWIFS for Iowa. However, that was not the case and thus further variables must have been affecting the differences. For Arkansas the drops in accuracy were increased over that of Iowa but still relatively minor. Both the band stripping and pixel degradation methodologies resulted in similar accuracy reductions. The 4-band scenario was down 1.9 percentage points from the original and the degraded pixel test lowered by a similar 1.7. Kappas trended down nearly equally as well. With the effects combined, the overall accuracy was 66.0 percent, down 3.4 points from the original TM. All of the degradation schemes for Arkansas yielded assessment values a bit lower than that produced from the raw AWIFS data outright. Finally, for the Illinois example there was a decrease in accuracy of only 0.6 for the 4-band scenario but almost three times greater with 1.7 for the 56 m simulation. The Kappa difference varied in the same manner and thus was more pronounced in change for the 56 m run. The combined impact to the two effects resulted in an accuracy drop of 2.2 percentage points. Unlike for the other study sites though, the compromised TM data for Illinois yielded impacts that were not damaging enough to reduce it below the output created from the raw AWIFS data. Taking a general average of all three cases, it appears that the change in spatial resolution has more impact on the classifier accuracy than the combined exclusion of the two spectral bands.

To boost the notion that the blue (band 1) and MIR (band 7) reflectance channels from TM were of little significance to the classification output, the relative importance of those spectral bands can be inferred by

Table 4. Overall Classification Assessments

	Arkansas		Iowa		Illinois	
Pixel based	TM	AWIFS	TM	AWIFS	TM	AWIFS
Accuracy (%)	69.4	68.4	59.1	61.6	75.8	70.8
Kappa	0.590	0.576	0.491	0.520	0.612	0.530

Table 5. Class Specific (a) Producer's, and (b) User's Accuracies (%)

(a)

Class	Arkansas TM	Arkansas AWiFS	Iowa TM	Iowa AWiFS	Illinois TM	Illinois AWiFS
Alfalfa	—	—	12.1	16.2	8.0	6.3
Corn	43.7	42.7	80.2	82.8	88.4	85.1
Cotton	71.7	75.3	—	—	—	—
Rice	82.6	84.1	—	—	—	—
Soybeans	79.4	76.5	76.1	71.4	82.9	75.1
Idle Cropland	14.4	10.1	54.0	49.2	4.3	1.4
Other Cropland	—	—	—	—	30.5	36.4
Pasture/Hay	34.0	29.3	61.9	66.1	7.9	14.1
Non-agricultural	—	—	37.2	45.4	—	—
Woodland	52.1	49.2	—	—	41.9	39.1
Developed	6.0	3.4	—	—	35.7	26.2
Water	17.3	20.4	—	—	—	—

(b)

Class	Arkansas TM	Arkansas AWiFS	Iowa TM	Iowa AWiFS	Illinois TM	Illinois AWiFS
Alfalfa	—	—	37.0	41.3	17.4	7.7
Corn	62.4	54.2	73.3	71.9	79.7	74.3
Cotton	69.9	74.1	—	—	—	—
Rice	83.1	84.5	—	—	—	—
Soybeans	69.1	66.1	68.5	72.9	80.3	74.3
Idle Cropland	40.8	26.5	44.3	42.3	4.1	1.1
Other Cropland	—	—	—	—	41.2	38.1
Pasture/Hay	29.8	22.6	37.6	42.0	35.1	39.3
Non-agricultural	—	—	69.1	73.5	—	—
Woodland	64.8	66.4	—	—	63.9	67.6
Developed	9.5	5.9	—	—	45.6	45.3
Water	17.9	23.2	—	—	—	—

studying the decision rules derived during the CTA. In other words, the bands with the least ability to discriminate between class types would be expected farther down the decision tree structure than the bands that were important. Within Iowa, and for both the raw TM and AWIFS data sources, NIR (band 4) was where the first decision was made and red (band 3) was the next most important. Blue was not needed until a split at the fourth level, and the MIR unused until even farther down the tree. This is consistent with there being little impact from those bands, since there was little change in the accuracy when they were taken out. For the Arkansas case, the primary split was based on the SWIR channel (band 5) in both TM and AWIFS. The NIR band was the next most important decision in the tree. Like with Iowa, the blue band was not called upon within the TM analysis until the fourth level of split, and the MIR layer was buried farther down. However, for Illinois, the story was different. Within the normal TM classification the blue band was utilized at the second level of the decision tree and the MIR band at the fourth. The red and near-infrared were found at the first and third split. For the corresponding AWIFS analysis, the SWIR band was called upon first and then the NIR. The overall implication was that the blue band provided more information than the MIR, and sometimes the blue band was as important as the red, NIR, and SWIR bands.

Table 6. Simulation of AWiFS Data from TM

	TM	4-band TM	56 m TM	4-band, 56 m TM	AWiFS
Arkansas					
Accuracy (%)	69.4	67.5	67.7	66.0	68.4
Kappa	0.590	0.564	0.569	0.546	0.576
Iowa					
Accuracy (%)	59.1	58.9	58.2	56.6	61.6
Kappa	0.491	0.488	0.479	0.456	0.520
Illinois					
Accuracy (%)	75.8	75.2	74.1	73.6	70.8
Kappa	0.612	0.599	0.586	0.575	0.530

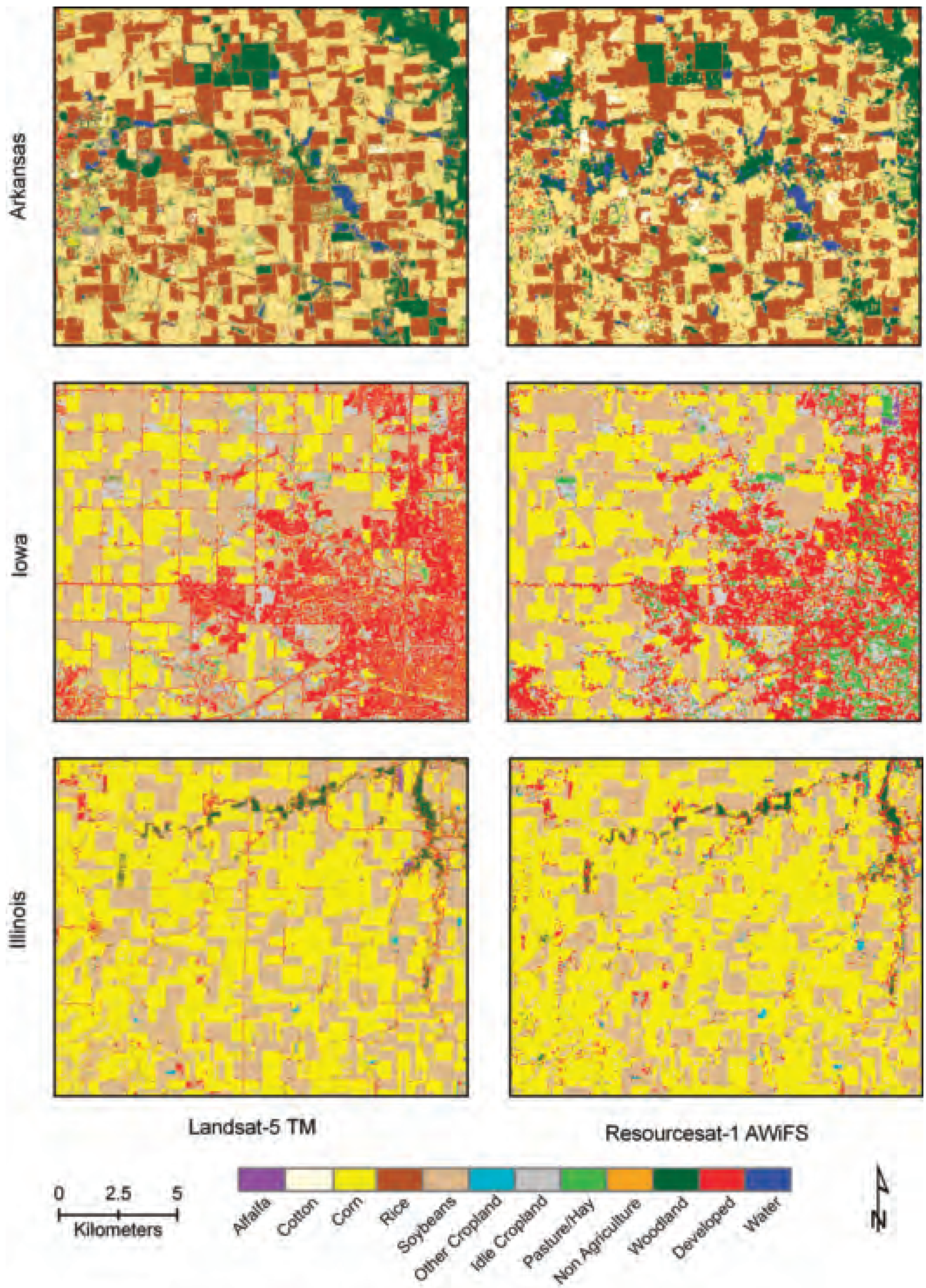

Plate 1. Classification output examples.

Discussion

The key classification objectives for NASS of good discrimination between cropland and non-cropland classes, and the within-cropland discrimination of major commodities, were met in most cases. The poorly performing non-cropland classes, regardless of sensor, may have seemed a disappointment, but are actually of little concern. Those categories are better served by more sophisticated classification efforts (e.g., NLCD or Gap Analysis) which may have been derived from ancillary raster or vector data (e.g., roads, water, field boundaries, and topography) and multiple scenes of time appropriate imagery (time series analysis over winter and summer). Even from a NASS perspective, cropland discrimination is known to improve with the availability of two or more scenes within the same growing season. This is how analysis within the CDL program is performed when possible.

Accuracy differences in general varied more widely across class categories than across sensor types. This was likely a reflection of insufficient training data or the spectral inconsistency of certain cover types. For example, the major row crop categories are usually planted, managed, and harvested similarly, and thus have steady multi-spectral reflectances ideal for classification. On the flip side, herbaceous cover types like alfalfa and hay often vary spectrally due to a range of cutting or grazing practices and thus were more difficult to properly categorize. Idle cropland-cover types often vary even more widely in practice because fallow fields can have vastly differing cover types, from bare soil to thick vegetation. Too few or non-representative training data was probably coming into play in the case of the mediocre result of the water class for Arkansas, which can vary from shallow aquaculture ponds to deep natural water bodies. For both the TM and AWIFS analysis, all of the poorly performing classes would likely be improved with the collection of more training data to better account for the true variability of those landscapes.

Furthermore, the pixel-based classification methodology used here was simplistic in nature and has room for improvement. An easy way to increase overall and within class accuracies is by taking spatial context into perspective through post processing of the results using a minimum mapping unit (MMU) filter to reduce spurious misclassified pixels. For example, applying a cropland appropriate MMU of 20 acres (8.1 hectares, or 90 TM pixels and 26 AWIFS pixels) to all of the example scenarios improved overall accuracies on average by a 5.2 percentage point difference for the TM examples and 4.0 with AWIFS. Kappas were also better for all cases averaging improvements of 0.064 for TM and 0.046 for AWIFS. The overall suggestion is TM has somewhat more to gain than AWIFS when increasing the MMU beyond the native pixel size due to its finer spatial resolution.

The overall accuracies in Iowa, with AWIFS outperforming the TM analysis, were somewhat surprising and perplexing. The explanation may be found in Iowa's uniqueness in terms of average surface incident angle of the scene pixels, compared to those from the Arkansas and Illinois study areas. Again, the Iowa TM data's area of interest was towards the left edge of the scene, facing away from the sun, while the corresponding AWIFS's data was angled oppositely, toward the sun. The resulting average difference in viewing angle was about 25 degrees. Given the better outcomes of AWIFS for Iowa, it can be speculated that the optimal bi-directional reflectance for discriminating cropland was looking into the sun and that the off-nadir increase in GSD was more than compensated for. The logic being impact from longer shadows found in certain cover types are mixing into pixels and thus increased contrast. This would be especially true for a crop like corn which in mid-August was tall and leafy versus a low lying category like pasture/hay. Analysis of full swath width AWIFS imagery does subjectively suggest that pixels towards the sun facing scene edges show more contrast between differing cover types, especially in the NIR and SWIR spectral bands. The wide range of view angles with AWIFS is something that should to be taken into consideration more heavily than when utilizing a relatively nadir looking system like TM. Viewing angle impacts on classification efforts is a research topic in its own right and needs to be further explored.

For agriculture regions outside those studied here, the negative impact of AWIFS larger pixels may become more dramatic in areas having smaller field sizes, such as those found in the eastern half of the U.S. It is speculated that the gap between AWIFS and TM performance would widen because scale would become more of an issue. Obviously, the larger and more uniform the field the less need there is for a high-resolution pixel to capture its difference from neighboring cover types. For data users that are focused on deriving non-agricultural classes, differences between TM and AWIFS may also become more apparent. Spatially detailed and texturally complex classes such as urban will likely suffer inferior classification results with AWIFS.

Only TM data in relation to AWIFS was compared within this study. Landsat-7 ETM+, scan-gap problem aside, is known to have better sensor performance than TM in terms of signal-to-noise ratio and the inclusion of the 15 m panchromatic band in addition to a 60 m thermal infrared. TM lacks both of these, and thus cropland classifications derived from a normally functioning ETM+ sensor would probably outperform TM, and thus AWIFS even more (Craig, 2002).

The large scene sizes of AWIFS are appealing because a large amount of training data can be employed, but they can have the unintended consequence of stretching training data information across the image to areas where they are not appropriate. Keeping agriculture as an example, training data from one scene corner of a particular commodity may have a difference spectral signature from that same commodity data several hundred kilometers away. This would be especially pronounced during the times of green-up or senescence where one portion of an image leads or lags another due to seasonal onsets. Also, crops may behave differently across scenes due to other geographic factors such as changes in soil types, soil moisture, elevation, climate, and crop management practices.

AWIFS offers compelling benefits over TM not addressed directly in a side-by-side classification comparison. For one, AWIFS has a much greater temporal repeat frequency. In a region like the mid-section of the U.S., one can expect cloud cover about fifty percent of the time during the summer. Haze is even more common. Often the biggest obstacle to being able to identify crops from space comes not from limitations due to sensor design, data infrastructure, or processing algorithms, but from the non-availability of suitable time appropriate imagery. NASS often finds occasions when not a single cloud-free TM scene is available during the growing season over certain areas. This results in an inability to produce a consistent wide area cropland classification. AWIFS with its five-day revisit rate more than triples the 16-day repeat of TM, and thus the likelihood of obtaining useable data. Furthermore, the same five-day repeat also increases the ability to capture multi-temporal data over the same location. Although only analysis of single scenes was shown here, improved classifications often result when two or more scenes from different times of the same growing season are used.

Second, because of the large AWIFS footprints, state-wide or regional scale classifications are simpler and more efficient to construct. For a typical U.S. state it takes several Landsat scenes to build a mosaic large enough to cover the entire area, and managing a large number of scenes with differing capture dates and atmospheric conditions increases the complexity and workload of a classification. With AWIFS, the potential exists for many state level projects to only need a couple of scenes to complete an entire analysis. Or thought of another way, utilizing the same amount of resources onto the larger scene footprints increases the scope of land in area that is classifiable. AWIFS is a tool that brings NASS closer to being able to rapidly identify planted locations of the major commodities beyond just a state level.

Another advantage to AWIFS is in regards to data intercomparability that can be had with the other LISS-III multi-spectral sensor on the Resourcesat-1 platform. It is collected simultaneously and has the identical sensor characteristics to AWIFS, other than a finer pixel size and narrower field of view. LISS-III allows for a direct method to obtain some of the AWIFS scene information spectrally calibrated at an increased resolution of 23.5 m. The JAS provides NASS with a rich training set of ground truth information, but other classification efforts might need to rely on inspection of higher resolution data that is collected in parallel.

Further utility of AWIFS data that TM cannot provide may arise in the form of time series analysis. Sensors such as AVHRR, MODIS, and SPOT Vegetation have typically been used for this work because they have a daily repeat frequency. However, their pixels have relatively low resolutions (250 m to 1 km) which are too large to provide detail at the crop field level for which Landsat is better suited. AWIFS represents a compromise between the low and medium resolution sensors in terms of temporal coverage and pixel size so has the potential for spatially detailed phenology analysis that is currently not possible.

Conclusions

A comparison of coincident Landsat-5 TM and Resourcesat-1 AWIFS imagery for deriving independent land-cover classifications emphasizing row crop agriculture has been presented for three study sites. TM data was found to be on average slightly superior to AWIFS in terms of overall, and within category, map accuracies. Differences were typically within five percentage points of one another and not considered major. TM performed better likely because of its spatial resolution being three and one half times finer than that of AWIFS and, to a lesser extent, the added spectral information provided through its blue and MIR bands. However, implying the only differences in the data sources were due to pixel sizes and spectral bands is likely over simplifying the comparison. This is true because it was shown degrading the TM data to match the AWIFS created larger, not smaller, dissimilarities between the outputs for two of the three cases.

It is speculated that the classification performance gap would widen if the study sites contained cultivated areas with fields smaller than those typically found within the central U.S. This is a logical next topic for research and would help document the usability of 56 m pixels in more spatially complex land-cover areas. Additionally, impacts to classification outcomes by AWIFS due to the wide field of view need to be explored in further detail. However, no evidence was found showing AWIFS edge pixels to be more compromised than those at nadir, and there is even suggestion that off-nadir viewing angles might have benefits.

For cropland classification purposes, it is believed the any loss in map accuracy from switching to AWIFS from TM will be compensated for by the threefold or better revisit rate. As such, Resourcesat offers real opportunity for temporal analysis of agriculture that Landsat cannot match. Answers to further crop questions, such as condition or yield, may become more obtainable from remotely sensed imagery than ever before.

Finally, while crop detection over the central U.S. was the focus here, there are obviously other applications and regions around the globe reliant on remotely sensed imagery of the earth's land surface. It is believed the large footprints and better than weekly overpass coverage of AWIFS can significantly increase the capacity of land-cover monitoring and evaluation for a variety of disciplines, particularly at regional scales. Users that will likely benefit most are those that have a difficult time obtaining imagery because of high likelihood of cloud cover in their area of interest such as in tropical, mountainous, or high latitude regimes. Additionally, because the large scene sizes simplify analysis, AWIFS data should be appealing to those in the land-cover monitoring community trying to map large regional or even continental-sized extents.

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