

# Use of Landsat ETM+ SLC-off Segment-based Gap-filled Imagery For Crop Type Mapping

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## Abstract

Failure of the Scan Line Corrector (SLC) on the Landsat ETM+ sensor has had a major impact on many applications that rely on continuous medium resolution imagery to meet their objectives. The USDA Crop Land Data (CDL) program uses Landsat data as the primary source of imagery to produce crop specific maps for approximately ten states in the U.S. A new method has been developed to fill the gaps, resulting from the SLC failure, to support the needs of Landsat users requiring coincident spectral data, such as for crop type mapping and monitoring applications. We tested the new gap-filled method for a CDL crop type mapping project in eastern Nebraska. SLC-off imagery was simulated on two Landsat 5 images (spring and late summer 2003) using 1992 and 2002 segment models (used in the gap-fill process). Various date combinations of original and gap-filled images were used to derive crop maps using a supervised classification process. Overall kappa values were slightly higher for crop maps derived from SLC-off gap-filled images as compared to crops maps derived from the original imagery (0.3% to 1.3% higher). Although the age of the segment model, used to derive the SLC-off gap-filled product, did not negatively impact the overall agreement, differences in individual cover type agreement did increase (-0.8% to +1.6% using the 2002 segment model to -5.0% to +5.1% using the 1992 segment model). Classification agreement also decreased for most of the classes as the size of the segment used in the gap-fill process increased.

## Introduction

On May 31, 2003, the Landsat ETM+ Scan Line Corrector (SLC) failed, resulting in the loss of approximately 22% of the normal scene area. The missing data affects most of the image with scan gaps varying in size from one pixel or less near the center of the image to 14 pixels along the east and west edges of the image, creating a wedge-shaped pattern. These images are referred to as SLC-off images whereas Landsat images collected prior to the SLC failure are referred to as SLC-on images (i.e., no data gaps exist). Even though spectral information in 78% of the image maintains the same radiometric and geometric quality as images collected prior to the failure (Storey *et al.*, 2005) the imagery can not be effectively used in many applications. The U.S. Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) uses Landsat as the primary source of imagery to produce crop specific maps in approximately ten states in the U.S. This program is referred to as the Cropland Data Layer (CDL) and currently produces crop maps for ten states that are utilized by a wide variety of applications (Craig 2001). The program currently uses Landsat 5 imagery to produce the crop maps; however the failure of this instrument could have severe impacts on the CDL program.

The US Geological Survey (USGS) Center for Earth Resources Observation and Science (EROS) has evaluated and tested several approaches to filling the gaps. Initial products were based on using radiometric adjustment techniques to compensate for the spectral changes between images. These products proved to be difficult to use in applications requiring same-day spectral information, such as crop mapping and monitoring applications which have a high rate of inter- and intra-annual spectral variability (Maxwell, 2004; Storey *et al.*, 2005). A new approach was recently developed by EROS, referred to as the segment-based gap-fill method, to meet the needs of applications that require same-day spectral data across the entire image such as the CDL.

The general concept of the segment-based gap-fill approach is to use a landscape model derived from SLC-on imagery (i.e., images collected prior to the SLC failure) to guide the interpolation of missing data in the SLC-off imagery (Maxwell *et al.*, submitted). The segment model is essentially a hierarchical set of landscape boundaries defining land units at different scales. The smallest landscape units are identified at scale 10 with median size of approximately 4.5 to 6.1 hectares depending on land cover type. Two additional larger scales, scale 15 and 20, delineate increasingly larger land units. Scale 10 boundaries are applied first to the SLC-off image to guide interpolation of spectral data across the gap pixels. Any remaining gap pixels are filled using the Scale 15 and 20 boundaries. And finally a cleanup process is applied to any remaining gap pixels. A thematic map is provided with the SLC-off gap-filled product that identifies the scale at which each gap pixel was filled.

The goal of this study was to determine if using the segment-based gap-filled imagery in classification of crops in a Midwestern US agricultural region significantly affects classification accuracy of the CDL ( $H_0: K_{\text{original}} < K_{\text{gapfilled}}$ ).

## **Approach**

The study area is in northeastern Nebraska covering approximately 16,000 square kilometers (latitude: 41.67 W; longitude: 96.67 N). This region is typical of Midwestern agricultural regions where row crops (69.6%) and hay/pasture (15.8%) dominate the landscape (USGS 1992 NLCD, <http://landcover.usgs.gov>). Patches of forest, grassland and riparian vegetation and developed areas occur throughout the region. Corn and soybeans are the dominant row crops (93.0% of row crops are corn or soybeans) in this region with minor crops of sorghum, oats, and wheat (USDA NASS, 2004).

Two images are normally used in the CDL processing. An early spring and late summer image are used to distinguish specific crop types from one another and cropped areas from non-cropped land cover types (e.g., forest, urban) (Craig, 2001). We used a spring image date of April 21, 2003 and a late-summer date of August 27, 2003 for this study. Both images were Landsat 5 scenes for Path 28 Row 31. The images were precision terrain corrected and georectified to UTM Zone 14 projection with nearest neighbor resampling at 30-meter resolution. SLC-off gaps were simulated on each of the Landsat 5 images to resemble Landsat ETM+ SLC-off images.

Table 1. Landsat images used in each test case.

Case #	Date of Segment Map	Spring Date used in Classification	Summer Date used in Classification
0	n/a	Original April 21, 2003	Original August 27, 2003
1	July 15, 2002	Gap-filled April 21, 2003	Original August 27, 2003
2	July 15, 2002	Original April 21, 2003	Gap-filled August 27, 2003
3	July 15, 2002	Gap-filled April 21, 2003	Gap-filled August 27, 2003
4	August 28, 1992	Gap-filled April 21, 2003	Original August 27, 2003

Five test cases were performed in our study (Table 1). All classifications were performed using a combination of the spring image (April 21, 2003) plus the late summer image (August 27, 2003). Test Case 0 was the *baseline* case where the original images (i.e., no gaps) were used in the classification process. Case 1 used an April SLC-off simulated gap-filled image plus the August original image. Case 2 used the April original image plus the August SLC-off simulated gap-filled image and Case 3 used gap-filled images for both the April and August dates.

Case 4 was designed to test the impact of landscape change on classification accuracy. The segment maps are created from circa 2000 imagery from the GeoCover data set. In our case, the date was July 15, 2002, only one year difference from our simulated SLC-off scenes. For Case 4, we tested the use of an older segment model to evaluate the impact of landscape boundary changes on crop map accuracy. A Landsat 5 image date of August 28, 1992 (11 year difference from the SLC-off simulated image use in our study) selected from the circa 1990 GeoCover data set, was used to create a second set of segment maps. The April 21, 2003 SLC-off simulated image was combined with the original August image to perform the classification.

SLC-off gaps were simulated on the Landsat 5 test images by applying a mask (0 = gap pixel, 1 = non-gap pixel). Gaps in SLC-off images do not normally occur in the same place for each scene date, therefore, the gaps were shifted on the second image by approximately 10 pixels to approximate a real-world case. Application of these gap masks to our two Landsat 5 images resulted in gap pixels covering 21.7% of the study area in the April image, 21.5% of the August image, and 37.5% in the combined April plus August images (Case 3). There was no overlap of the gap areas between the two scenes where gap widths were seven pixels or less. The gaps overlapped from one to six pixels as the gap widths increased; with a six pixel overlap at the outer edge of the scene.

The training and test data used for this research was a subset of data collected from the NASS operational program known as the June Agricultural Survey (JAS). The JAS is a national survey based on a stratified random sample of land areas selected from each state's area sampling frame (ASF) (Bush and House, 1993). The NASS ASF's are land use stratifications based on percent cultivation. The selected areas, known as segments, are targeted mainly toward cultivated strata of each state although every strata area has a possibility of selection at the state level.

Table 2 The 2003 JAS samples for the study area target area.

Strata*	Population (# pixels)	Sampled Segments (#)	% Cultivated
11	7043	32	> 75
12	1093	10	51-75
20	161	1	15-50
31-50	n/a	53	0-15

\* Stratum 11 segments are approximately one square mile each, while strata 12 and 20 segments are two square miles. The data from strata 31-50 were small user selected windows for specific non-agricultural cover types such as urban, woodland, and water. No JAS sample segments from these strata fell in the target area.

Field boundaries within the segments were user reviewed against current year satellite imagery for consistency problems. Any obvious problem fields were marked as "bad for training". Also deleted from the training data set were those pixels touching or within one pixel of a field boundary or any pixels from small fields (under 10 acres). Cover type specific files of pixels from the remaining "good" data were then created. A maximum of 10,000 pixels were randomly sampled and then clustered with a modified ISODATA algorithm. The signatures for each cover type were then written together into one final signature file. This final file was used in a maximum likelihood classifier procedure to categorize the entire target area. Percent correct and Kappa statistics were generated based only on the "good" pixels. All accuracy measurements are presented as Kappa statistic values.

Table 3. Training data. Classes noted under the 'Primary Classes' column were used for test case comparisons.

Primary Classes		Other Classes			
Class	# pixels	Class	# pixels	Class	# pixels
Corn	13,904	Permanent pasture	2,703	Farmstead	198
Soybeans	8,137	Urban	2,241	Cropland pasture	66
Woods	3,856	Idle crop	1,587	Winter wheat	61
Non-agriculture	3,759	Water	1,114	Other hay	35
Alfalfa	995	Wooded pasture	227	Wild hay	31
		Other minor crops	202	Oats	29

The training data consisted of seventeen cover types (Table 3). For comparison purposes, we selected the three largest crop covers (corn, soybeans, and alfalfa) and the two largest non-crop covers (woods and non-agriculture); together these accounted for over 78% of the segment area. Other covers, including permanent pasture, urban, idle cropland, water, wooded pasture,

farmstead, cropland pasture, winter wheat, other hay, wild hay, oats, and other minor crops are included in the overall measures of accuracy but not shown individually. Although crop covers are usually well defined, some of the non-crop cover types have vague definitions. For example, permanent pasture may differ from non-agriculture only in the sense that livestock has access to it. Similar vague definitions exist between woods and wooded pasture, and farmstead versus non-agriculture. Idle cropland can also be easily confused with other covers.

## Results and Discussion

Overall agreement between the ground reference data and the classified map generated from the original 2-date Landsat data set, referred to as the *baseline* map or Case 0, was 89.3% with individual class agreements ranging from 75.3% (non-agriculture) to 99.2% (alfalfa) (Figure 1). Overall classification kappa values for the crop maps generated from gap-filled images (Cases 1-4) generated slightly higher kappa's (0.3% to 1.3% higher) (Table 3). Therefore our null hypothesis was rejected since the crop maps using the gap-filled imagery resulted in higher kappa values than the land cover map generated from original imagery.

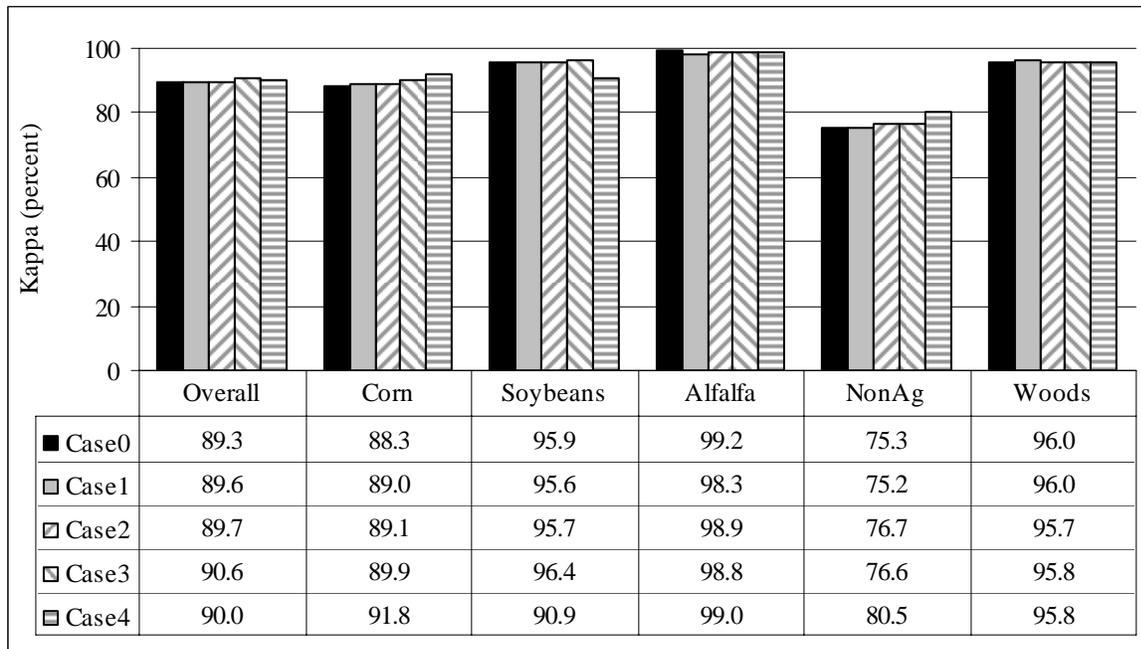


Figure 1 Overall and individual class agreement between the ground reference data and classified maps for all test cases.

Table 4 Comparison of kappa statistics for four land cover maps derived from gap-filled images to a land cover map derived from non gap-filled imagery. Comparison is significant at p-value < .05.

	Case #	Overall Accuracy	Kappa Accuracy	Standard Error	Case #'s Compared	Z-score	Significant
Overall Classification	0	.914	.893	.015			
	1	.917	.896	.015	0,1	1.22	N
	2	.917	.897	.014	0,2	1.59	N
	3	.924	.906	.013	0,3	5.17	Y
	4	.919	.900	.016	0,4	2.52	Y

Review of the classified maps and gap-filled images revealed that the increase in agreement was likely caused from the ‘smoothing’ effect in the spectral values of the gap pixels resulting from the gap-fill process. Figure 2 shows a comparison of the original April image (left) to the gap-filled image (right). The smoothing effect of the gap-fill process can be seen where the mixture of darker and lighter cyan colored pixels is replaced by only light colored cyan pixels (circled areas). Spectral heterogeneity is reduced for gap pixels since the gap-fill process basically repeats the spectral values of dominant pixels across the gap space within a specific landscape unit defined by the segment boundary. As our study area is predominantly crop fields, the smoothing would tend to reduce within field spectral variability resulting in less misclassified pixels within individual fields.

Reduced variability in the overall image spectral statistics was also noted, where all bands in the April image and three of seven bands (bands 1, 2 and 3) in the August image had a reduction in spectral variability for gap-filled pixels as compared to non gap-filled pixels (range -0.2% to -2.6%). Comparison of the classified maps for the same area show the majority of pixels are classified as corn in the map derived from the gap-filled imagery (right), whereas the map derived from the original imagery displays a mixture of corn and soybean pixels (left). Although the smoothing effect of the gap-fill process appeared to be slightly advantageous in our case as it resulted in reduced within-field variability, applications that rely on spectral heterogeneity to classify land cover types, such as impervious surface mapping, may find the smoothing effect has a negative impact on those cover types – especially toward the east and west edges of the scene where gaps are largest (up to 14 pixels wide).

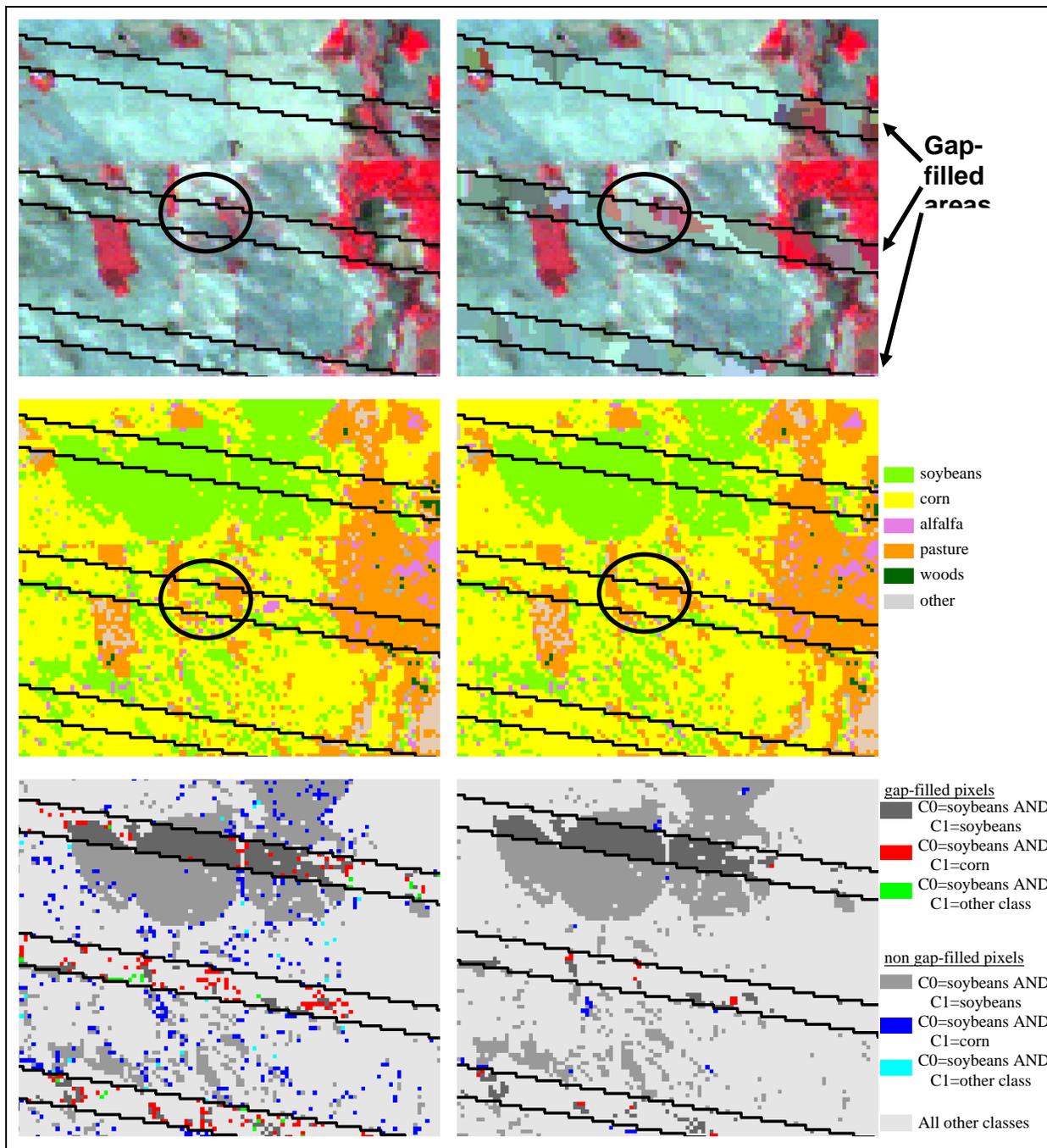


Figure 2 Comparison of Case 0 results (no gap-fill imagery used) to Case 1 (April SLC-off simulated gap-filled image used in classification). Top row: April 23, 2003 original image (left) and SLC-off simulated gap-filled image (right). Middle row: Classification map for Case 0 (left) and Case 1 (right). Bottom row: Case 0 and Case 1 difference map before filtering (left) and after application of a 3 by 3 filter (right). Circles indicate areas where the number of individual scattered pixels of soybeans (green) within predominantly corn areas (yellow) were reduced. C0=Case 0, C1=Case1. Heavy black lines represent border of gap areas.

The majority of differences between the baseline map and test case maps were individual pixels as opposed to larger clumps of pixels. For example, 84.0% of the pixels classified as soybeans in the Case 0 map were also classified as soybeans in the Case 1 map (Figure 2 lower left; medium and dark gray areas). The majority of the remaining pixels in disagreement were labeled as corn in the Case 1 map (80.0%) (Figure 2; red and blue pixels). After a 3 by 3 majority filter was applied to the difference map (filter was applied only to the pixels classified as soybeans in the Case 0 map and classified as a different cover type in the Case 1 map), the number of pixels classified as soybeans in the Case 0 map and not soybeans in the Case 1 map were reduced by 81.5% across the entire map (Figure 2, compare red, cyan and blue pixels in the lower left difference map to the lower right difference map). Disagreement between the two maps was not just isolated to gap-filled pixels. Of the pixels classified as soybeans in the Case 0 map and classified as corn or another cover type in the Case 1 map, 67.5% were not gap-filled pixels, indicating that the spectral properties of the training signatures were influenced by the gap-filled pixels falling within training areas. Again, however, these pixels were generally isolated and scattered as opposed to large landscape patches or entire crop fields being misclassified.

The largest differences between the baseline map and the test case maps for individual cover types were found in test Case 4; the test case where the April 21, 2003 SLC-off image was filled using the older 1992 segment model. Differences in kappa values for individual cover types ranged from -5.0% (soybeans) to +5.1% (non-agriculture) for test Case 4; whereas kappa's ranged -0.8% to +1.6% for test cases that used SLC-off gap-filled images derived from the more recent 2002 segment model was applied (Cases 1, 2, and 3) (Figure 1).

The Case 4 map contained 14.6% more soybean classified pixels as compared to Case 1. A large proportion of these pixels (81.9%) were outside the gap-filled area suggesting the training statistics were impacted in Case 4 to a greater extent as compared to Case 1. Evaluation of the gap-filled sample pixels showed that mean difference DN values were higher in general for Case 4 (range 0.02 to 1.45 absolute difference) as compared to Case 1 (0.01 to 0.73 absolute difference) across all bands. The fully automated classification process of the CDL and tight security associated with the location of the ground reference data precluded us from confirming this in our study. In any case, exclusion of gap-filled training pixels from the training sample selection was not a viable option for the CDL program due to the limited amount of training sites. We do however, recommend that training data collected within gap-filled regions be closely inspected to ensure outliers are eliminated prior to using for classification.

Area differences between the baseline map and the maps generated using gap-filled images were the highest, in general, for Case 4 where the older 1992 segment model was applied. Difference in area between the baseline map and the maps derived from SLC-off gap-filled images where the 2002 segment model was applied (Cases 1, 2, and 3) ranged from -6.3% (Case 3; woods) to +6.4% (Case 3; corn) for individual classes (Figure 3a); whereas are difference for Case 4 ranged from -11.9% (woods) to +11.5% (soybeans). The highest differences in area were in the gap-filled pixels. Area differences (absolute) for the gap-filled pixels were 4.0% higher, on average, as compared to non-gap pixels (Figure 4 b, c). The largest differences were in the woods class, where differences were 15.3% to 27.8% higher in the gap-filled areas for Cases 1, 2, and 3 as compared to the non gap-filled areas. Average absolute area difference was 2.3% for corn, soybeans, alfalfa and non-agriculture across all test cases (maximum difference was 6.9%).

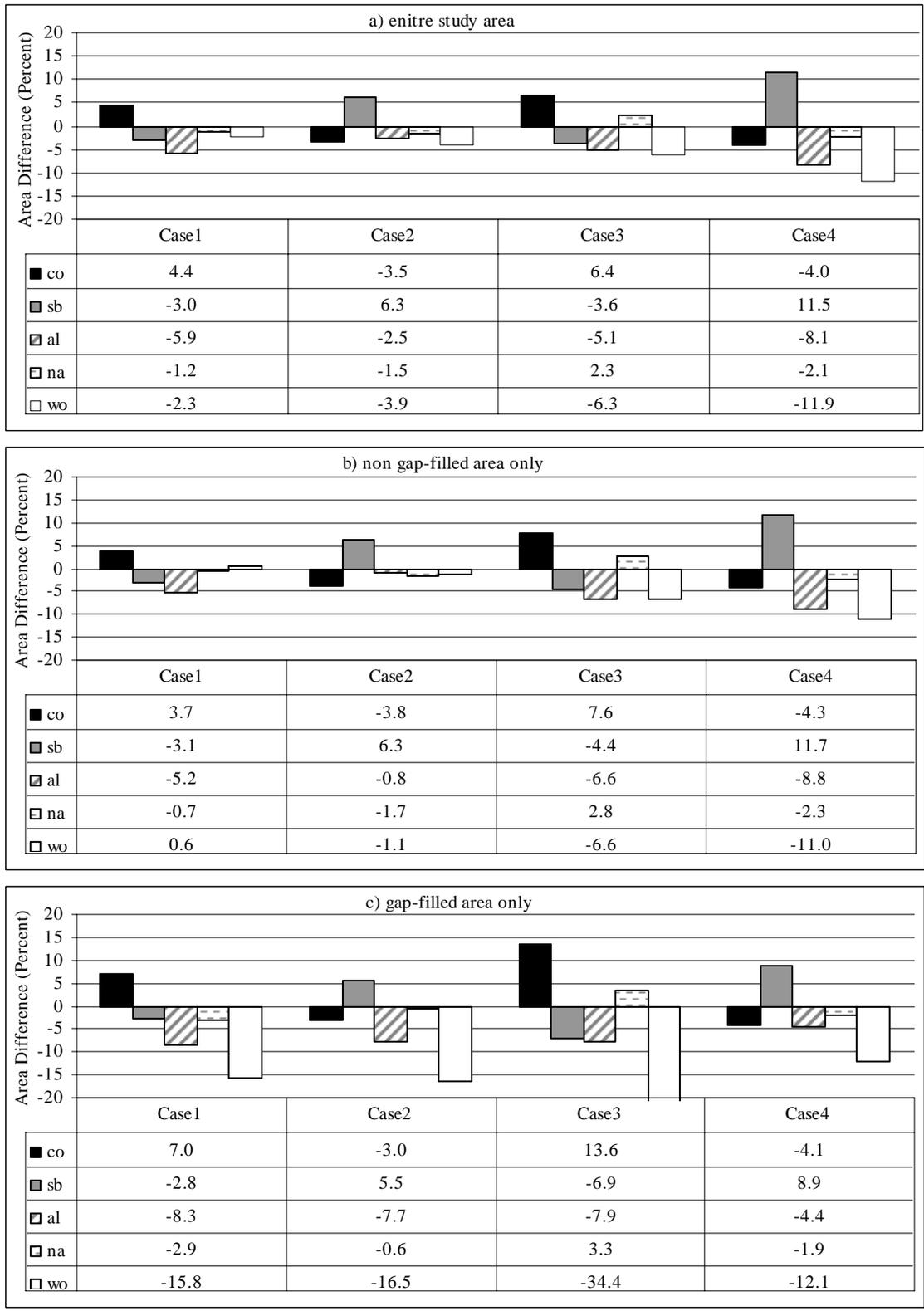


Figure 3 Comparison of area difference (percent) between Case 0 classified maps (original images) and each test case (1=spring gap-filled+summer original, 2=spring original+summer gap-filled, 3=spring gap-filled+summer gap-filled, 4=spring gap-filled using 1992 segment map+summer original) for major crop and land cover classes for a) entire study area, b) non gap-filled areas only, and c) gap-filled areas only.

Comparison of the original spectral values to predicted spectral values of the gap-filled pixels revealed that spectral differences increased as the scale of segments used to fill the gaps increased. The mean Pearson product moment correlation coefficient for gap pixels filled at scale 10 ranged from 0.79 to 0.88 (bands 1-5 and 7) across the three images (Figure 4). Mean correlation values decreased to between 0.52 to 0.66 for pixels filled using scale 15 segments and decreased further to 0.43 to 0.56 for pixels filled using the scale 20 segments. Correlation coefficients for pixels filled at scale 99 were the lowest ranging from 0.40 and 0.32. Correlation coefficients were generally higher in the images filled using the more recent segment model (2002).

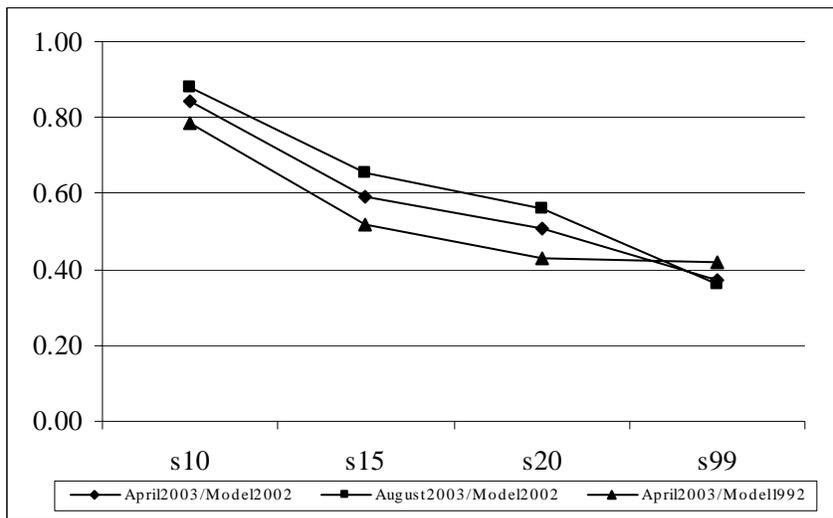


Figure 4 Correlation between original and predicted gap pixels for each segment model scale for each of the three Landsat SLC-off gap-filled images tested; April 21, 2003 and August 27, 2003 gap-filled using 2002 segment model and April 21, 2003 gap-filled using a 1992 segment model. Mean computed for bands 1-5 and 7. N=1000.

Given the negative relationship between scale and correlation between original and predicted spectral values, we expected greater classification errors in gap pixels at the higher scales. Comparison of percent agreement for each class in Case 0 to the test cases at each segment scale revealed that differences were fairly stable across all scales for the non-agricultural class (range 70.0-75.8% agreement) yet all other classes showed a substantial decrease in percent agreement for pixels filled at scales 15, 20 and 99 as compared to pixels filled at scale 10 (Figure 5). Soybeans, alfalfa and woods classes showed the largest decreases between 18.4% and 36.0% in percent agreement in scale 15 pixels as compared to scale 10 pixels (mean percent agreement for all test cases). Although the largest percentage of gap-filled pixels are filled using the scale 10 segment model (approximately 84.0%, Maxwell *et al.*, submitted), the user should be aware of the potential for larger errors in pixels filled using the higher segment scales.

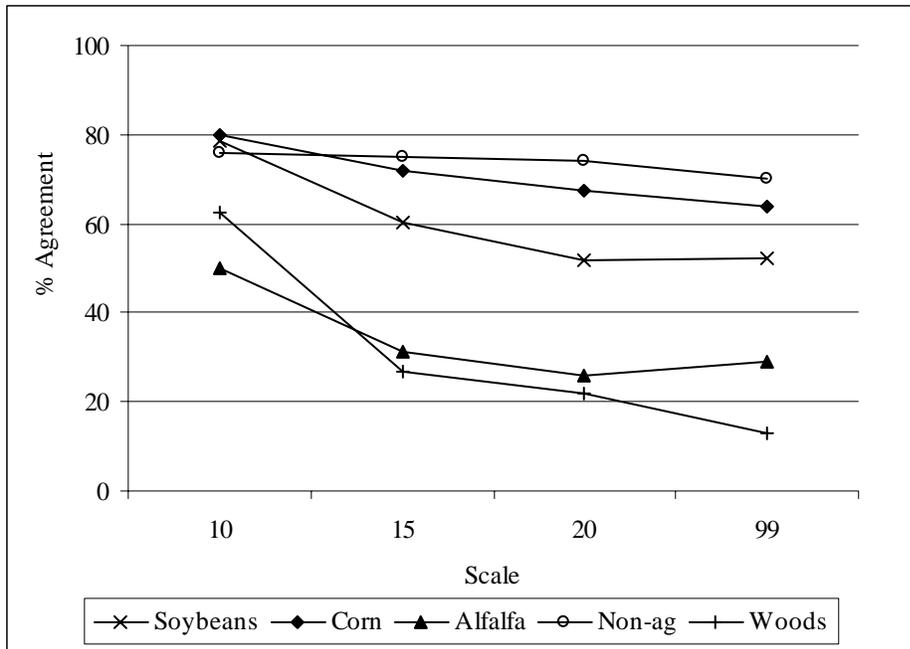


Figure 5 Percent mean agreement for each class and each segment scale for gap-filled pixels only.

## Summary

This study tested the use of Landsat SLC-off segment-based gap-filled imagery for a crop type mapping application in eastern Nebraska. Gaps were simulated on two Landsat 5 image dates (April 23, 2003 and August 21, 2003) and used in various 2-date combinations of original and gap-filled image data sets in a supervised classification. In addition to testing the 2002 segment model, normally used to generate the gap-fill product, we also tested the use of a 1992 segment model to determine the impact of landscape changes on map accuracy. Our study found that there was no decrease in overall map agreement using gap-filled images. Overall classification kappa values for all the test cases were slightly higher (0.3% to 1.3%) than the original map. This slight increase was likely the result of reduced spectral variability of gap-pixels (resulting from the gap-fill algorithm) which in turn resulted in reduced within-crop field variability. Although the ‘smoothing’ effect of the gap-fill process appeared to be slightly advantageous in our case, applications that rely on spectral heterogeneity to classify land cover types, such as impervious surface mapping, may find the smoothing effect has a negative impact – especially toward the east and west edges of the scene where gaps are largest (up to 14 pixels wide). Most of the differences between the map produced with the original images (non-gap filled) and the maps produced using gap-filled imagery were individual scattered pixels as opposed to larger landscape patches. We also found that errors increased as the time difference increased between the date that the segment map was created (circa 2000) and the date the SLC-off image was collected. Classification agreement also decreased as the size of the segment used in the gap-fill process increased. We recommend that gap-filled pixels be closely evaluated when used for development of training statistics and that the larger segment scales (e.g., 15, 20 and 99) be used as an indicator of lower accuracy in resulting crop maps.

## **Acknowledgements**

## **References**

Bush, J. and House, C., 1993, The area frame: a sampling base for establishment surveys, Proceedings of the International Conference on Establishment Surveys, Buffalo, New York, June 28-30, 1993, pp. 335-344.

Craig, M.E., 2001. The NASS Cropland Data Layer Program. Proceedings of the Third International Conference on Geospatial Information in Agriculture and Forestry, Denver Colorado, November 5-7, 2001, CD-ROM.

Maxwell, S.K., 2004, Filling Landsat ETM+ SLC-off gaps using a segmentation model approach, Photogrammetric Engineering and Remote Sensing, 70(10), 1109-1111.

Maxwell, S.K., Schmidt, G., Storey, J., submitted. A multi-scale segmentation approach to filling gaps in Landsat ETM+ SLC-off images, submitted to International Journal of Remote Sensing, January 2006.

Storey, J., Scaramuzza, P., and Schmidt, G., 2005, Landsat 7 scan line corrector-off gap-filled product development, Pecora 16 Conference Proceedings, 23-27 October 2005, Sioux Falls, South Dakota.

US Department of Agriculture, 2004. 2002 Census of Agriculture, Washington, D.C.

US Geological Survey, 1992. 1992 National Land Cover Data Set. Retrieved September 2004, <http://landcover.usgs.gov>.