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Forest Cover Index for Tree Cover Detection Using Landsat-7 Multispectral Imagery

Luisa I. Feliciano-Cruz, Sarah J. Becker, Kristofer D. Lasko,
Craig S.T. Daughtry, and Andrew L. Russ

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Forest Cover Index for Tree Cover Detection Using Landsat-7 Multispectral Imagery

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Abstract

Forest cover monitoring using satellite imagery is important to U.S. military terrain analysis. Mobility models, cover and concealment, and precise surface feature delineation all rely on an accurate forest/non-forest cover layer. However, the challenge remains in distinguishing trees from other vegetative land covers when relying on single date imagery. A Forest Cover Index (FCI) algorithm was previously developed on Worldview-2 imagery and was designed to separate forest cover from non-forest covered areas. In this research, the FCI algorithm was applied to Landsat-7 imagery using the analogous red (636–673 nanometers (nm)) and near-infrared bands (851–878 nm) from a peak summer image on 16 August 2012. The results obtained with Landsat-7 imagery proved satisfactory with an overall accuracy (tree cover versus non-tree cover) of > 83 percent, according to testing with two different accuracy assessment tests. The application of the FCI to Landsat-7 imagery broadens the applicability of the FCI to freely available imagery.

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Preface

This work was performed by the Geospatial Analysis at the Tactical Edge, Geo-enabled Augmented Intelligence for Decisive Engagement, and Geo-Intelligence in Complex Urban Environments work packages under projects Geospatial Analysis at the Tactical Edge (GATE), 405906 and 405908, Geo-enabled Augmented Intelligence for Decisive Engagement (GAIDEN), 0602784A-855-24, and Geo-Intelligence in Complex Urban Environments (GeoICUE), 62784.

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COL Teresa A. Schlosser was Commander of ERDC, and Dr. David W. Pittman was the Director.

Unit Conversion Factors

Multiply	By	To Obtain
acres	4,046.873	square meters
acre-feet	1,233.5	cubic meters
cubic feet	0.02831685	cubic meters
cubic inches	1.6387064 E-05	cubic meters
cubic yards	0.7645549	cubic meters
degrees (angle)	0.01745329	radians
feet	0.3048	meters
hectares	1.0 E+04	square meters
inches	0.0254	meters
miles (nautical)	1,852	meters
miles (U.S. statute)	1,609.347	meters
slugs	14.59390	kilograms
square feet	0.09290304	square meters
square inches	6.4516 E-04	square meters
square miles	2.589998 E+06	square meters
square yards	0.8361274	square meters
yards	0.9144	meters

Acronyms and Abbreviations

BARC	Beltsville Agricultural Research Center
DoD	Department of Defense
ENVI	Environment for Visualizing Images
ESRI	Environmental Systems Research Institute
FCI	Forest Cover Index
GRL	Geospatial Research Laboratory
m	meter
NDVI	Normalized Difference Vegetation Index
nm	nanometers
ROI	Regions Of Interest
USACE	U.S. Army Corps of Engineers
USDA	U.S. Department of Agriculture

1 Introduction

The mapping of forest cover in heterogeneous land-use images is challenging because forest cover can be indistinguishable from other types of vegetation in multispectral imagery (Becker et al. 2018). Healthy forest cover demonstrates a similar spectral profile to other healthy green vegetation with variations based on vigor, water content, and cell structure (Becker et al. 2018; Knipling 1970). Prior research has explored techniques to map forest cover using *index* and *classification-based approaches*, as described in section 1.2, but has fallen short in consistently detecting tree cover in complex environments.

1.1 Objective

The objective of this project is to apply the Forest Cover Index (FCI) algorithm, FCI2, to Landsat-7 multispectral imagery. This will provide scientists and researchers, who do not have access to DigitalGlobe WorldView multispectral satellite imagery, the opportunity to employ the FCI for forest cover detection using freely-available multispectral imagery.

The specific project objectives are the following:

- Test the FCI workflow for forest canopy detection using freely available Landsat-7 multispectral imagery in both ArcGIS (Environmental Systems Research Institute (ESRI), Redlands, California) and Environment for Visualizing Images (ENVI) software (Harris Corporation, Melbourne, Florida). The imagery will be from the U.S. Department of Agriculture (USDA) Henry A. Wallace Beltsville Agricultural Research Center (BARC) near Beltsville, MD (39.025° N, 76.850° W).
- Perform an accuracy assessment of the results using a non-random sampling technique comparing results to known vegetative land cover polygons to generate a performance (confusion) matrix including user's, producer's, and overall accuracy, and the Kappa statistic (Appendix A).
- Conduct a more robust accuracy assessment using a stratified-random sampling technique with unbiased areal proportions, and compare with the non-random technique.

- Automate the workflow for the forest cover indices using ArcGIS ModelBuilder.

1.2 Approaches

1.2.1 Index-based approaches

The Normalized Difference Vegetation Index (NDVI), as well as similar vegetation indices have been developed as indicators of vegetation greenness or health in remotely-sensed imagery (Rouse et al. 1974) and have been used to delineate vegetative from non-vegetative land covers (Jackson and Huete 1991; Kaplan and Avdan 2017). Even though these indices monitor forest states and canopy processes (Jinguo and Wei 2004; Huete 2012), none has been found to consistently aid in distinguishing between forest cover and other vegetative land cover classes. For example, Bunting and Lucas (2006) focused on tree cover and applied red edge and red band ratios, and selected the maximum value in imagery and achieved accuracies ranging from 19.2 to 91.6 percent in delineating tree crowns depending on the stem diameter at breast height.

1.2.2 Classification-based approaches

Other researchers have employed supervised and unsupervised classification techniques to identify forest cover in imagery with varying degrees of success, with forest cover often confused with agriculture or rangeland (Yuan et al. 2005; Ye et al. 2014; Akar et al. 2017). For a comprehensive literature review on prior research in mapping forest cover in multispectral imagery, please see Becker et al. (2018).

1.3 Scope

Becker et al. (2018) addressed the need to detect forest cover in imagery by developing two FCI algorithms that reliably distinguish trees from other types of vegetation in two meter (m) spatial resolution WorldView-2 multispectral imagery at the BARC. This research expands on the results reported by Becker et al. (2018) applying the FCI to 30-m Landsat-7 multispectral imagery to distinguish forest cover from other vegetated land cover classes.

2 Project Background and Description

This research developed a methodology for distinguishing forest cover from other land cover types using moderate resolution multispectral imagery. Since traditional vegetation indices and classification techniques do not consistently separate out tree from other land covers, as described in section 1, two forest cover indices, FCI_1 and FCI_2 , were developed by Becker et al. (2018) to separate forest from other land covers. Becker et al. (2018) found that by multiplying reflectance in the red and red edge, as well as in the red and near-infrared bands, a delineation between trees and other vegetative land covers was observed. The FCIs are shown in the following equations:

$$FCI_1 = R_{660} * R_{725} \quad (1)$$

$$FCI_2 = R_{660} * R_{835} \quad (2)$$

Where, R_{660} , R_{725} , and R_{835} represent reflectance in red, red edge, and near-infrared bands, respectively (Becker et al. 2018).

Becker et al. (2018) conducted the initial test at the BARC (Figure 1). The site is comprised of 2,500 hectares of intermixed agricultural fields, pastures, conifer and deciduous woodlands, wetlands, and some urban areas. Typical soil has a sandy-textured surface layer and a taxonomic classification of coarse-loamy, siliceous, mesic Typic Hapludults (Soil Survey Staff 2018). The study site is located in the coastal plain and consists of fairly flat to gently sloping uplands. The climate is humid subtropical with precipitation occurring throughout the year (Weatherbase 2018).

Figure 1. Landsat-7 image of the Beltsville Agricultural Research Center (BARC) in Beltsville, MD, outlined in red from 16 August 2012.



Becker et al. (2018) developed the FCI's using WorldView-2 multispectral imagery. The seasonality of the tree cover was measured by selecting one date for each season: 27 May 2012, 05 Aug 2012, 26 Oct 2014, and 18 Jan 2013. Once the forest cover indices were applied to the imagery, a threshold for separating Tree vs. Not Tree was manually obtained through trial and error. This threshold was then used to produce a masked image.

Our research expands upon the research by Becker et al. (2018) by testing the workflow used for the initial study with freely-available Landsat-7 multispectral imagery. Landsat-7 contains reflectance bands in the visible through thermal infrared regions of the electromagnetic spectrum but does not include a red edge band, the workflow will only test the applicability of FCI₂ on Landsat-7 imagery.

3 Project Methodologies

According to the specific objectives of the research defined in section 1, the project methodologies are cataloged as 1) Landsat-7 FCI test and accuracy assessment using ground truth based on vegetation types obtained in the field, and 2) an accuracy assessment using stratified-random points and high resolution satellite imagery (i.e., Worldview-2).

3.1 Landsat-7 FCI workflow and accuracy assessment from purposive sampling of vegetation regions of interest (ROI)

This research tested the workflow outlined in Becker et al. (2018) on Landsat-7 red and near infrared bands acquired on 16 August 2012. The FCI₂ equation as applied to Landsat-7 is as follows:

$$FCI_2 = R_{655} * R_{865} \quad (3)$$

Where, R_{655} and R_{865} represent reflectance in red and near infrared bands, respectively. While this research was tested using ENVI Classic software, the user can perform the following steps in a preferred remote sensing software package:

1. Apply the FCI₂ algorithm to the Landsat-7 image to generate the FCI₂ image.
2. Examine different land covers in the FCI₂ grayscale image to determine a user-defined threshold value that separates trees from other vegetation covers.
3. Build a mask to separate trees below the threshold value.
4. Apply the mask to the original image, resulting in an image that masks all of the tree pixels.

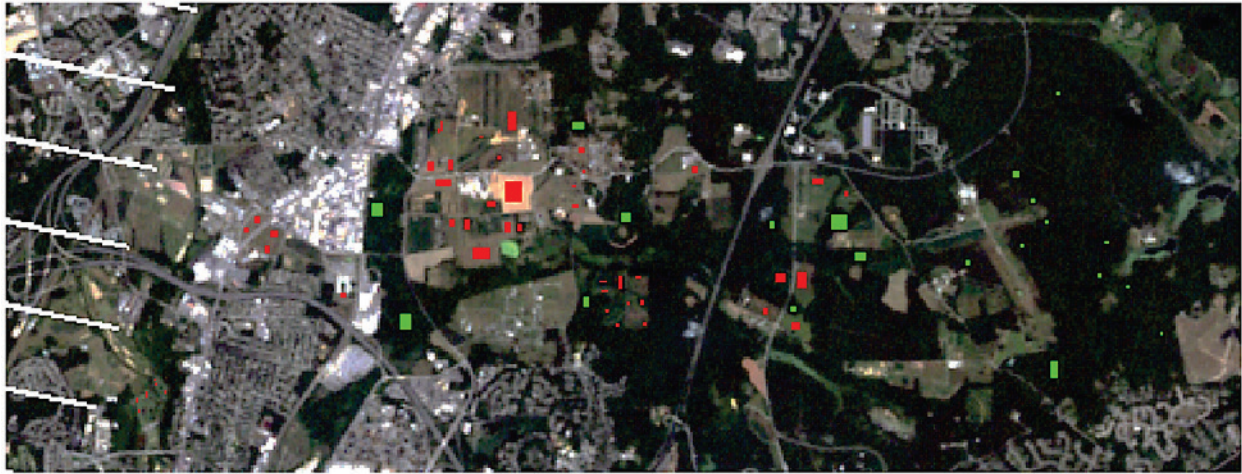
The accuracy assessment applied to this research measures the agreement between a classified image generated through remote sensing analysis against reference data (i.e., ground-truth data or high-resolution imagery) that is anticipated to be correct. For this research, 2-m WorldView-2 imagery was used as reference data. This is usually performed through a confusion matrix, yielding an overall accuracy and the Kappa statistic. According to Congalton and Mead (1986), confusion matrices also describe the errors of inclusion (commission errors as measured in the user's accuracy) and errors of exclusion (omission errors as measured in

the producer's accuracy) present in a classified image. A commission error occurs when a pixel is incorrectly included in the class to which it does not belong, and an omission error occurs when a pixel is excluded from the class to which it belongs (Congalton and Green 2009). In summary, every error on the classified image is an omission from the correct class or a commission to an incorrect class. This analysis aids in obtaining an overall accuracy, which in the confusion matrix is the sum of the major diagonal (i.e., the number of correctly classified pixels) divided by the total number of pixels in the image.

To generate a confusion matrix, the user identifies regions of interest (ROI) from ground truth data and compares the ROIs to the classified data. For this research, two classes were created, "Tree" and "Not Tree," containing 66 ROI polygons (Figure 2). The Tree category included ten conifer and ten deciduous ROIs. The "Not Tree" category included thirty ROIs of annual crops (alfalfa, barley, corn, orchardgrass, rye, ryegrass, soybean, turf grass, triticale, and wheat), ten perennial grass pastures, and six golf courses. The ROIs were identified using a non-random purposive sampling technique, where the researcher had prior knowledge of the ROIs and selected them to represent the diverse array of vegetative land cover classes throughout the image. Using a non-random sampling technique, such as the purposive sampling technique, is less robust and introduces bias, which makes results appear better than they actually are. The technique was selected to ensure a variety of vegetative land cover classes were included and compared to forest cover. Including this technique also gives the ability to compare accuracy with the stratified random sampling technique, as discussed in the section below.

Kappa is a statistic that measures agreement between the classified and ground truth images (Cohen 1960; McHugh 2012; Congalton et al. 1983). Landis and Koch (1977) assigned ranges for Kappa to categorize agreement. According to Landis and Koch (1977), Kappa values greater than 80% represent strong agreement, values between 40–80% represent moderate to substantial agreement, and values below 40% represent poor agreement.

Figure 2. Landsat-7 image of the BARC from 16 August 2012 showing the Tree (green) and Not Tree (red) ROIs.



3.2 Stratified-random points accuracy assessment

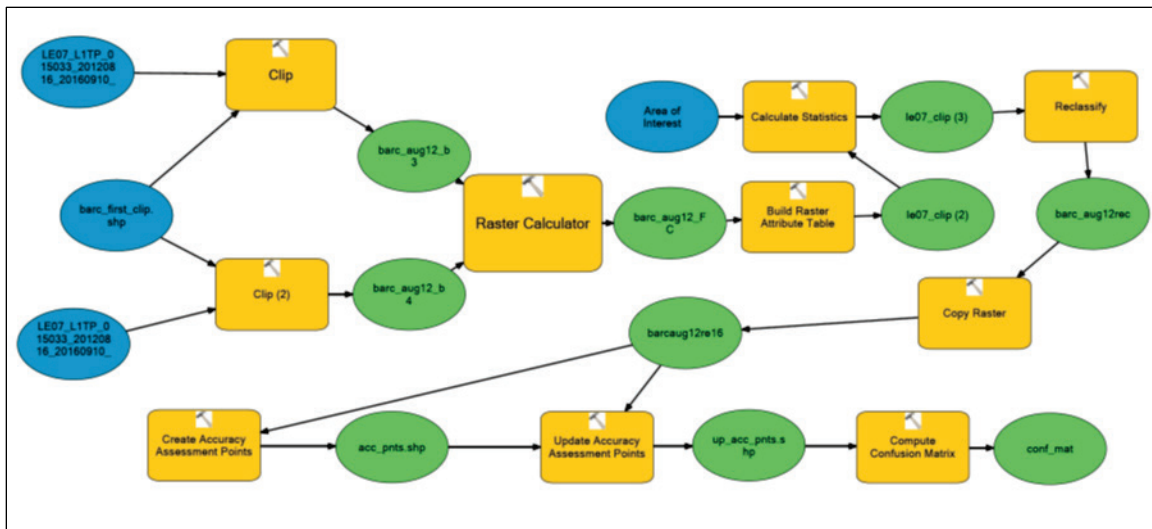
The second accuracy assessment was conducted using land covers based on a stratified-random sample of points for all land cover types in the Landsat-7 image with WorldView-2 as reference data. Multinomial probability sampling was used to calculate how many points are needed. The number of sample points, N , is determined by:

$$N = \frac{B\Pi_i(1 - \Pi_i)}{b_i^2} \quad (4)$$

Where, Π_i represents the proportion of a population in the i^{th} class out of k number of classes, b is the precision, and B is the upper $(\alpha/k)*100$ th percentile of the chi-square (X^2) distribution with one degree of freedom (Congalton and Green 2009). The number of sample points are divided amongst the different classes in proportion to their area.

To generate the confusion matrix, the initial ROIs are replaced by a set of random points for classification and ground truth data. The workflow involves the following three ArcGIS geoprocessing tools: Create Accuracy Assessment Points, Update Accuracy Assessment Points, and Compute Confusion Matrix (ESRI 2018). A semi-automated workflow was constructed in ArcGIS ModelBuilder for computing the FCI_2 and the confusion matrix in the stratified-random point accuracy assessment (Figure 3).

Figure 3. Schematic of the ModelBuilder workflow for stratified-random point accuracy assessment.



4 FCI Results and Accuracy Assessments

The workflow to apply the FCI₂ to Landsat-7 imagery yielded raster output where the trees were masked out of imagery and other land covers remained visible (Figure 4). The resulting confusion matrices (purposive sampling and random sampling) for the classifications are included in Appendix A. Table 1 and Table 2 summarize the accuracy assessment for the 66 ROIs. Depending on the accuracy assessment type, the overall accuracy ranged from 83.7% to 95.5% with Kappa of 67.5% and 90.6% representing agreement between classification and ground truth data. Dark vegetation, such as dense agriculture, was misclassified as forest cover in some instances because the FCI₂ values for agriculture overlapped with forest values. Even though dense agriculture was present throughout the image, the FCI₂ still successfully differentiated between most of it and forest cover. Some non-vegetative dark pixels, such as water bodies, were also misclassified as forest cover in the result, which led to a decrease in accuracy.

Figure 4. This figure shows the result of the FCI₂. Forest cover was masked out of the image and other land covers remained visible.

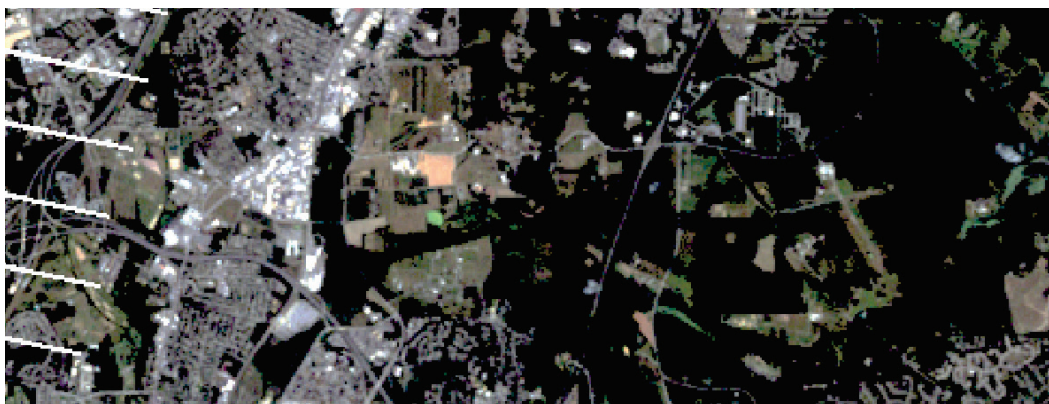


Table 1. Landsat-7 results for user's, producer's, and overall accuracy, as well as the Kappa statistic for FCI₂ using purposive sampling.

Date	Class	Accuracy (%)			Kappa	Variance
		Producer	User	Overall		
16 August 2012	Tree	99.9	89.2	95.5	90.6	0.0026
	Not Tree	92.8	99.9			

A total of 422 sample points were generated based on multinomial probability sampling theory and the chi square distribution with parameters of 1 degree of freedom, a precision of 5% and $k = 2$ classes,

with 95% confidence intervals. The two classes were points selected from either Tree or Not Tree classified areas, depending on the area proportions in the resulting map. Since the classified image contains 64,247 Tree pixels, and 27,288 Not Tree pixels, the study area represents about 70% Tree and 30% Not Tree. Points laying on the study area's scanline errors were removed, ultimately obtaining 419 sample points. Since there is roughly 70% Tree, then there should be $419 \times 70\% = 293$ points representing Tree and $419 \times 30\% = 126$ points representing Not Tree. Figure 5 shows the resulting stratified-random points for the BARC and Table 2 shows the accuracy assessment. Red represents Not Tree, while the green represents Tree ground truth points.

Figure 5. Stratified-random points for accuracy assessment. Red represents Not Tree, while the green represents Tree ground truth points.



Table 2. Landsat-7 results for user's, producer's, and overall accuracy, as well as the Kappa statistic for FCI₂, employing stratified-random accuracy assessment points.

Date	Class	Accuracy (%)			Kappa	variance
		Producer	User	Overall		
16 Aug 2012	Tree	77.8	91.8	83.7	67.5	0.0027
	Not Tree	91.1	76.3			

5 Discussion

This study tested an algorithm originally developed for high-resolution WorldView-2 multispectral imagery to differentiate forest from other vegetative land covers using medium-resolution Landsat-7 imagery. The results showed the FCI₂ can reliably separate forest from other vegetative land cover classes in a leaf-on Landsat-7 image of Beltsville, MD. The scene included dense forest, agricultural, and urban land cover.

Becker et al. (2018) calculated accuracy statistics using purposive sampling of vegetative ROIs of WorldView-2 imagery and their results were similar to the accuracy using Landsat-7. These results suggest Landsat-7 is a viable alternative when WorldView-2 is not available and when finding individual trees with high resolution imagery is unnecessary.

Prior research has shown that differences in reflectance between the forest canopy and an individual leaf occur because of variations in illumination angle, leaf orientations within the canopy, shadowing, and non-foliage backgrounds present in the image (Knipling 1970). Furthermore, shadowing decreases the spectral response of vegetated pixels (Zhang et al. 2015), which could lead to the lower FCI₂ values used to identify forest pixels.

Further testing is suggested to validate the technique in other locations and across changing image dates. This technique was not tested in areas with sparse tree cover or tree species not present in Beltsville, MD. It is also recommended to test the impact of a preliminary image segmentation that separates vegetated from non-vegetated pixels. For example, the NDVI can be used to mask non-vegetative pixels from the image, which could improve the accuracy of the assessment that used stratified-random points because the FCI₂ would then only separate tree from other vegetative cover types. Non-vegetative dark pixels, such as water, will no longer be misclassified as forest cover.

6 Conclusions

The use of Landsat-7 imagery yielded good overall accuracy results. FCI₂ was successfully applied to freely-available Landsat-7 imagery providing researchers and scientists the ability to employ the FCI without purchasing commercial imagery. A typical WV-2 image with 5% or less cloud cover is available for \$20 per 1 square kilometer (or 0.37 square miles), which would be around \$2,000 for the BARC imagery (Land Info 2018). The results suggest applying the FCI₂ to Landsat-7 to detect forest cover could be an alternate to using WorldView-2 to find forest cover when individual trees are not of interest and WorldView-2 is not available.

The overall accuracy for the purposive sampling with ROIs technique was 95.5% with a Kappa of 90.5. The stratified-random points accuracy assessment with unbiased areal proportions provided improved overall accuracy for FCI₂ at 83% with a Kappa statistic of 67.5% which is within the acceptable range.

Future research will focus on FCI₂ testing across seasons in diverse terrain and within different forest types. Future accuracy assessments will apply the stratified-random points accuracy assessment technique using unbiased areal proportions as it provides an assessment which is proportionally representative of the entire study area.

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Appendix A: Confusion Matrix for Landsat-7, 16 August 2012, Calculated With ENVI Classic

Figure A1. Output matrix trial.

output matrix trial

Confusion Matrix: G:\ERDC GRL Material\ENVI\ROIclassvalassig

Overall Accuracy = (380/398) 95.4774%

Kappa Coefficient = 0.9055

	Ground Truth (Pixels)		
Class	ROI:NOT TREE	ROI:TREE	Total
Unclassified	0	0	0
NOT TREE [Blu	232	0	232
TREE [Red] 51	18	148	166
Total	250	148	398

	Ground Truth (Percent)		
Class	ROI:NOT TREE	ROI:TREE	Total
Unclassified	0.00	0.00	0.00
NOT TREE [Blu	92.80	0.00	58.29
TREE [Red] 51	7.20	100.00	41.71
Total	100.00	100.00	100.00

Class	Commission (Percent)	Omission (Percent)	Commission (Pixels)	Omission (Pixels)
NOT TREE [Blu	0.00	7.20	0/232	18/250
TREE [Red] 51	10.84	0.00	18/166	0/148

Class	Prod. Acc. (Percent)	User Acc. (Percent)	Prod. Acc. (Pixels)	User Acc. (Pixels)
NOT TREE [Blu	92.80	100.00	232/250	232/232
TREE [Red] 51	100.00	89.16	148/148	148/166

Table A1. Confusion matrix for stratified-random accuracy approach, Landsat-7, 16 August 2012, calculated with ArcGIS using unbiased areal proportions.

		Tree	No Tree	Total	Pixels(Map)	UA	UA CI
	Tree	0.6443	0.0576	0.7019	64247	91.79%	0.28%
	No Tree	0.0707	0.2274	0.2981	27288	76.28%	0.39%
	Total	0.7150	0.2850	1.0000	91535		
Unbiased areal estimate	Area(ha)	5,890.36	2,347.79				
Error amount (ha)	S(area)ha	134.46	134.46				
Error amount (CI)	95%	263.55	263.55				
Adjusted producer's accuracy	PA	90.11%	79.79%				
CI for PA	PA CI	0.3%	0.4%				
Overall Accuracy	87.17%						

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14. ABSTRACT Forest cover monitoring using satellite imagery is important to U.S. military terrain analysis. Mobility models, cover and concealment, and precise surface feature delineation all rely on an accurate forest/non-forest cover layer. However, the challenge remains in distinguishing trees from other vegetative land covers when relying on single date imagery. A Forest Cover Index (FCI) algorithm was previously developed on Worldview-2 imagery and was designed to separate forest cover from non-forest covered areas. In this research, the FCI algorithm was applied to Landsat-7 imagery using the analogous red (636–673 nanometers (nm)) and near-infrared bands (851–878 nm) from a peak summer image on 16 August 2012. The results obtained with Landsat-7 imagery proved satisfactory with an overall accuracy (tree cover versus non-tree cover) of > 83 percent, according to testing with two different accuracy assessment tests. The application of the FCI to Landsat-7 imagery broadens the applicability of the FCI to freely available imagery.					
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