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Mapping trees outside forests using high-resolution aerial imagery: a comparison of pixel- and object-based classification approaches

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Abstract Discrete trees and small groups of trees in nonforest settings are considered an essential resource around the world and are collectively referred to as trees outside forests (ToF). ToF provide important functions across the landscape, such as protecting soil and water resources, providing wildlife habitat, and improving farmstead energy efficiency and aesthetics. Despite the significance of ToF, forest and other natural resource inventory programs and geospatial land cover datasets that are available at a national scale do not include comprehensive information regarding ToF in the United States. Additional ground-based data collection and acquisition of specialized imagery to inventory these resources are expensive alternatives. As a potential solution, we identified two remote sensing-based approaches that use free high-resolution aerial imagery from the National Agriculture Imagery Program (NAIP) to map all tree cover in an agriculturally dominant landscape. We compared the results obtained using an unsupervised per-pixel classifier (independent component analysis—[ICA]) and an object-based image analysis (OBIA) procedure in Steele County, Minnesota, USA. Three types of accuracy assessments were used to evaluate how each method performed in terms of: (1) producing a county-level estimate of total tree-covered area, (2) correctly locating tree cover on the ground, and (3) how tree cover patch metrics computed from the classified outputs compared to those delineated by a human photo interpreter. Both approaches were found to be viable for mapping tree cover over a broad spatial extent and could serve to supplement ground-based inventory data. The ICA approach produced an estimate of total tree cover more similar to the photo-interpreted result, but the output from the OBIA method was more realistic in terms of describing the actual observed spatial pattern of tree cover.

Keywords Trees outside forests · Forest inventory · Tree cover · Aerial photography · Object-based image analysis · Independent component analysis

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Introduction

Trees outside forests (ToF) are considered an important land use feature in a global context and have now been included as an attribute of interest in the United Nations' Global Forest Resource Assessment. By definition, ToF are "trees on land not defined as forest and other wooded land" (FAO 2001); examples include trees that occur on agricultural and grazed lands, along waterbodies and roads, and in residential and urban settings (Rawat 2003). In large portions of the central United States where agriculture dominates the landscape, tree cover exists primarily as ToF. Although scarce in terms of overall coverage, ToF provide a variety of ecological benefits, including protecting soil and water resources, providing wildlife habitat, and improving farmstead energy efficiency and aesthetics (Rietveld and Irwin 1996) and providing biomass for carbon sequestration (Schoeneberger 2005; Kort and Turnock 1999).

While the importance of ToF is recognized, a continual inventory and monitoring program for the resource does not exist in the United States. National Forest Inventories (NFIs) typically rely on minimum size and density requirements to define forests and thus do not collect information on ToF. For example, the Forest Inventory and Analysis (FIA) program of the US Department of Agriculture Forest Service defines forest to be land with a minimum of 10 % tree cover (or equivalent stocking) and is at least 1 acre in size (USDA Forest Service 2010). Furthermore, the area must be at least 120 ft, or 36.6 m, in width, thus excluding narrow tree plantings and many naturally occurring tree corridors along streams. A study by Perry et al. (2009) found that the estimate of total tree-covered area would exceed the estimate of forestland by at least 25 % in the Great Plains region if tree resources such as ToF were included in the FIA inventory.

We do note, however, that information has been collected periodically on ToF in the United States for limited geographic areas (Hartong and Moessner (1956) in Iowa; Hansen (1985) in Kansas; and Lister et al. (2009) in the Great Plains). While each of these studies relied on aerial photography and/or ground-based sampling specifically targeted at ToF, several efforts have been made to use satellite imagery to comprehensively map land cover across the conterminous US (e.g., the National Land Cover Dataset (NLCD 2006) (Xian et al. 2009)). In these cases, the sensors used are too coarse to discern small groups or narrow tree plantings and do not provide consistent estimates of total tree cover (Perry et al. 2009; Liknes et al. 2010). In contrast, digital aerial imagery is typically collected at a very high spatial resolution (e.g., ≤1 m) and is sufficient to capture small patches of trees and even individual tree crowns. The resolution, however, presents a challenge since a higher spatial resolution leads to increased spectral variation of landscape features, which makes it more difficult to statistically separate classes using traditional pixel-based classification methods and thus reduces classification accuracy; this is known as the 'H-resolution problem' (Woodcock and Strahler 1987 and Marceau et al. 1990 *in* Hay et al. 1996). As such, the challenge warrants the development of new methodologies for working with this type of imagery. Two more recent options are object-based image analysis (OBIA) and independent component analysis (ICA).

Image segmentation and classification are the two main components of OBIA approaches. Segmentation is the process used to divide the imagery into homogeneous image segments, or objects, which become the processing units that are subsequently classified rather than the individual pixels (Benz et al. 2004). The image segments are groups of similar, adjacent pixels formed to represent the landscape features of interest (e.g., agricultural fields, houses, and roads). User-defined settings of shape, color, compactness, and scale parameter determine what that resulting image objects will look like. The scale parameter is a unitless number that sets the degree of heterogeneity within the image objects, so a larger-scale parameter will result in larger, more heterogeneous image objects (Laliberte et al. 2007; Benz et al. 2004). The OBIA method is different from classic pixel-based procedures that rely solely on the pixel spectral values represented by digital numbers (DNs) to classify each pixel individually. OBIA procedures offer several fundamental advantages over per-pixel approaches: (1) image objects can be created at various scales (e.g., from a single tree crown to groups of trees) (de Jong and van der Meer 2004; Hay 2003), (2) the use of image objects alleviates the salt-and-pepper effect often encountered in pixel-based classifications (Yu et al. 2006), and (3) numerous attributes can be obtained from image objects, including statistics such as mean and standard deviation using the DNs (Chubey et al. 2006). In addition, classification results based on image objects have been found to be more accurate than those from pixel-based procedures (Blaschke and Strobl 2001; Benz et al. 2004; Yu et al. 2006; Platt and Rapoza 2008; Myint et al. 2011).

While the OBIA approach has been found to produce more accurate classification results, standard OBIA-specific accuracy assessment procedures are lacking (Drăguţ and Blaschke 2006) and this remains a "hot" research topic within OBIA (Blaschke 2010). Persello and Bruzzone (2010) suggest an accuracy assessment approach "that is based on the analysis of two families of indices: (1) the traditional thematic accuracy indices and (2) a set of novel geometric indices that model different geometric properties of the objects recognized in the map." However, this does not appear to be widely implemented at this time. The common practice found in the literature is the continued use of accuracy assessment methods that were developed for per-pixel methods, including error, or confusion, matrices and the use of descriptive statistics, such as user's and producers accuracies (e.g., Congalton 1991). In addition, many OBIA studies use stratified random (or proportional) sampling to select points, plots, or objects from which to create the reference data set (e.g., Myeong et al. 2001; Laliberte et al. 2007; Johansen et al. 2007; Zhou et al. 2009; Myint et al. 2011; Peña-Barragán et al. 2011).

Although OBIA techniques such as 'Extraction and Classification of Homogeneous Objects' (ECHO) have been in existence for more than 30 years (Kettig and Landgrebe 1976), their use in extracting information from high-resolution imagery has increased markedly during the last decade; this is coincident with the increase in availability of such imagery from both satellite and aerial platforms (see Blaschke (2010) for a thorough discussion of historical and more recent OBIA research). There are numerous studies where OBIA procedures were used to produce output classifications related to natural resources. A review of the literature reveals that high-resolution imagery and OBIA have been used in conjunction as an approach for mapping woody plant features in agricultural and other rural landscapes around the globe. For example, Tansey et al. (2009) used OBIA to accurately identify hedgerows with a 2-m minimum width from aerial imagery in Berkshire, UK. Aksoy et al. (2010) carried out a study in Germany, the Czech Republic, and Cyprus in which an object-based methodology was used to automate the process of identifying linear wooded strips in agricultural areas. Other related studies include juniper cover estimation from NAIP imagery in Idaho, USA (Davies et al. 2010) and Wiseman et al. (2009) where large shelterbelts were mapped over an area covering approximately 25,900 ha using very high-resolution (62.5 cm) aerial imagery in Manitoba, Canada. The authors concluded that an object-based method was very efficient for broad-scale inventorying of shelterbelts. However, these studies were confined to small geographic areas while more recent examples that use OBIA techniques occur over much larger areas, such as 289,755 ha in North Dakota, USA (Liknes et al. 2010) and 177,000 ha in California, USA (Peña-Barragán et al. 2011). The recent use of OBIA techniques offers a promising solution to the challenge of mapping fine-scale tree features from digital aerial imagery over a large spatial extent in the central United States.

Unlike OBIA, ICA, which is a pixel-based classification approach, is a less conventional technique that reduces the dimensionality of the input data. It was developed as a type of blind source separation (Common 1994; Hyvärinen and Oja 2000) whereby input signals could be separated into source signals without any knowledge of the original inputs. Recently, ICA has been used for unsupervised classification (Shah et al. 2007b) and pan sharpening (Chen et al. 2011), and it has been implemented in ERDAS IMAGINE® (Shah et al. 2007a), a popular image processing software package.

ICA is often compared and contrasted with the more well-known principal component analysis (PCA). One major difference is the order of statistics used; that is, ICA makes no assumption that original source components follow a Gaussian distribution and uses skewness and kurtosis to determine the independence of input sources. The two data reduction methods are often compared; for example, Wang and Chang (2006) found that ICA-based dimensionality reduction outperformed PCA-based methodology when used with AVIRIS and HYDICE hyperspectral image data, and ICA has been used for land cover classification in the State of Iowa (e.g., ftp://ftp.igsb.uiowa.edu/gis_library/counties/lyon/HRLC_2007_60/HRLC_2007_60.html#7).

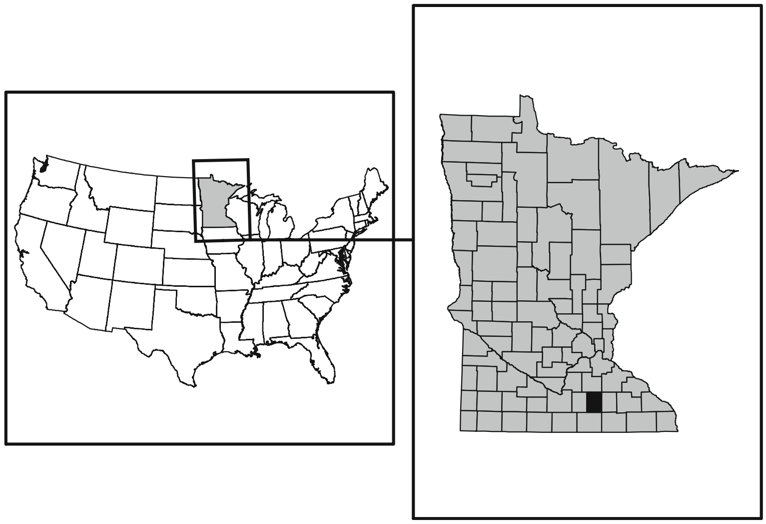
Given the need for more comprehensive information regarding ToF, the objective of this study was to investigate the aforementioned approaches as potential solutions for broad-scale mapping of all tree cover (ToF and forest) in agricultural landscapes from very high-resolution aerial imagery. The results offer a means for supplementing NFIs by providing information on the extent of ToF with a particular focus on methods that are efficient and at least partially automatable so that the mapping process could become a recurring part of an NFI and therefore serve to monitor trends in ToF.

Materials and methods

Study area

Steele County, located in southern Minnesota, USA, was selected as the study area (Fig. 1). The county is

Fig. 1 Location of Steele County in southern Minnesota, USA



nearly 111,000 ha in size and the landscape is similar to that found throughout the central United States. The dominant landscape feature is row-crop agriculture, and other cover types include trees, farmsteads, urban development and roads, rivers, and lakes. The city of Owatonna is the county seat and about two-thirds of the county's population resides there. The non-urban portion of the county is comprised of 934 farms according to the 2007 Census of Agriculture (USDA National Agricultural Statistics Service 2009).

High-resolution imagery

Digital aerial imagery from the US Department of Agriculture's Farm Service Agency National Agriculture Imagery Program (NAIP) was obtained for this study. NAIP imagery is collected during the growing season (leaf-on) primarily for agricultural compliance monitoring and has been captured on a routine basis since 2003. The return interval varies by state, and datasets from 2003 (1 m), 2004 (2 m), 2005 (2 m), 2006 (2 m), 2008 (1 m), 2009 (1 m), and 2010 (1 m) exist for the state of Minnesota. Data from 2008 were used because of the availability of the near-infrared (NIR) spectral band in addition to the normally acquired red, green, and blue bands. Images were obtained in uncompressed TIFF format and had been divided into a series of 49 tiles with 300 m of overlap between adjacent images. The tiles have a variety of image acquisition dates from throughout the growing season (June, July, or August).

Input data layers for the OBIA and ICA approaches were obtained or derived from the NAIP imagery and included the red, green, blue, and NIR spectral bands, the normalized difference vegetation index (NDVI), and a green texture band. NDVI is derived using the NIR and red bands from the imagery where the difference between the two is divided by the sum of the two bands. The index is commonly used for identifying vegetation and can be used for other purposes such as identifying stressed versus healthy vegetation (Tucker and Choudhury 1987). However, its use in this study was simply to add other useful information for detecting tree cover. While NDVI is useful for identifying vegetation in general, trees needed to be discriminated from other surrounding vegetation, so the use of texture layers was incorporated. Texture is a way to measure the visual roughness versus smoothness of features in an image (Haralick et al. 1973; Lillesand et al. 2008) and is important for distinguishing tree cover from other vegetation, such as grassy lawns (Zhang 2001 in Tansey et al. 2009; Myeong et al. 2001).

OBIA approach

The workflow for the OBIA approach is shown in Fig. 2. The segmentation and classification routines were carried out using eCognition Developer software v. 8.0.1 (Definiens 2010). A trial-and-error approach and visual inspection of the results was employed in order to determine which user-defined settings produced the most meaningful image objects in order to meet our study objectives. To begin, the 'multiresolution segmentation' algorithm was used to segment

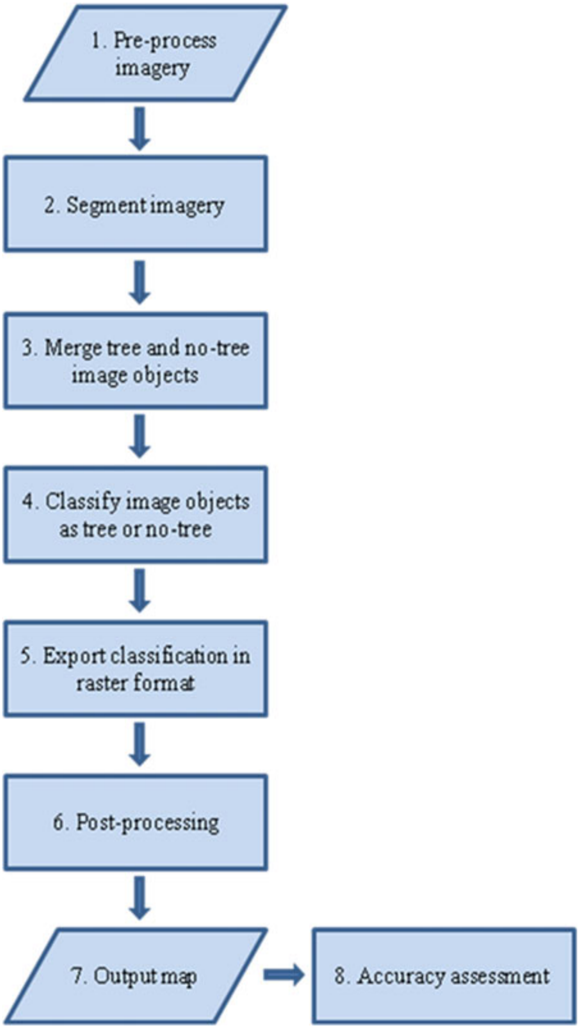


Fig. 2 Object-based image analysis workflow for classifying NAIP imagery into tree and no-tree classes. ArcGIS® and ERDAS IMAGINE® software were used in *Step 1* to pre-process the imagery. *Steps 2* through *5* run sequentially in eCognition software and processing multiple images was automated using a programming script. *Steps 6*and *7* were carried out using a python™ script

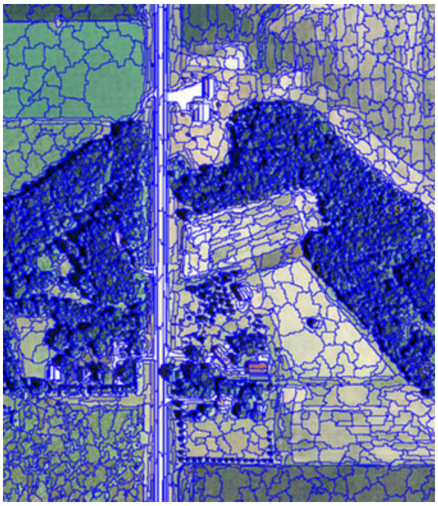


Fig. 3 Example of Level 1 image objects created in eCognition from NAIP imagery in Steele County, MN

each image tile into fine-scale image objects (called "Level 1") with the following settings: scale parameter = 15, shape = 0.2, and compactness = 0.9 (Fig. 3). A second level ("Level 2") of larger image objects was then created using a scale parameter of 20 and the Level 1 image objects as building blocks, and all subsequent processing occurred on the Level 2 image objects. This was done in order to reduce the very large number of Level 1 objects for more efficient successive processing. More emphasis was given to color (0.8) rather than shape (0.2) during the segmentation processes and only the four spectral bands were utilized to create the Level 1 and Level 2 image objects. Compactness was set high (0.9) so more circular-shaped image objects were created in an attempt to better represent the shape of tree crowns. The NDVI and texture information were utilized in subsequent steps for separating tree from no-tree image objects. The segmentation/classification routine was developed for one image tile and then applied to the remaining 48 images using a programming script to automate the processing.

The primary goal during segmentation was to maintain image objects that were purely tree canopy, whether it was a single tree crown or continuous canopy. This was accomplished using a series of thresholds and an increasing scale parameter to iteratively merge the no-tree objects into larger and larger objects (e.g., farm fields) by capitalizing on the NDVI and texture information. The tree image objects were also aggregated using the 'multiresolution segmentation region grow' algorithm to make larger, more continuous canopy objects and reduce the total number of image objects. Typically, there would be more than 200,000 Level 1 image objects reduced to about 2,000 per image tile using this process (Fig. 4a). There are many image object attributes (spectral, spatial, and textural) that can be incorporated during the segmentation and classification processes. In this study, the processes relied primarily on the following attributes (using the mean value for the image object) to

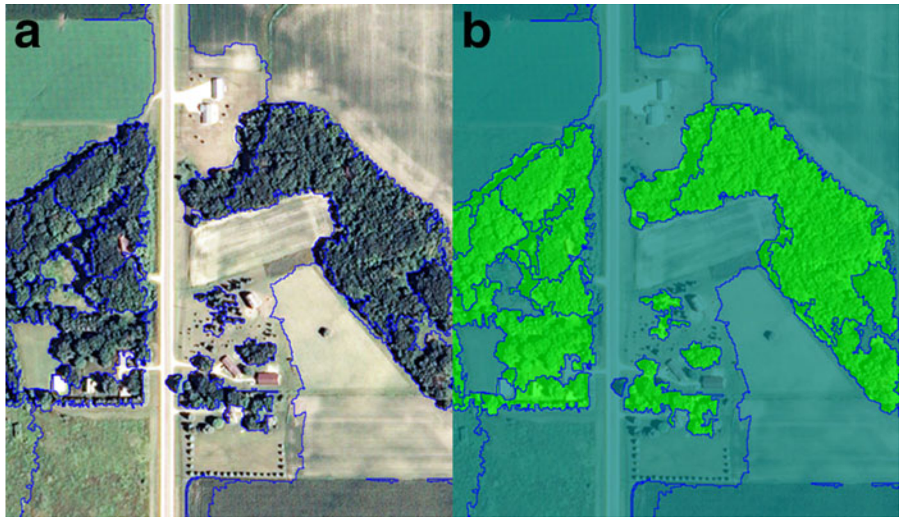


Fig. 4 **a** and **b** Final level of image objects (**a**) and classification of final level of image objects created in eCognition from NAIP imagery in Steele County, MN; 'tree' objects are represented in green color (**b**)

distinguish tree cover from the no-tree image objects: brightness (combined value of the red, green, and NIR input bands), texture of the green band and NDVI, and values of each of the four spectral bands.

During the classification phase, image objects were assigned to one of two classes: tree or no-tree (Fig. 4b). Classification rules were developed using mostly the features listed in the previous paragraph. Thresholds were developed using observed feature information for no-tree objects compared to that of tree objects. We used lower mean values of the visible bands (red, green, blue) and brightness, and higher mean NDVI, NIR, and green texture values to distinguish tree cover from the surrounding areas. Classification results for each image tile were exported in raster format. ArcGIS® Desktop v.9.3.1 software (ESRI Inc. 2009) was used to mosaic the 49 raster outputs together and then clip the compiled output to the county boundary and convert it to vector format. Lastly, the estimate of total tree-covered area for the county was obtained by calculating the area of the 'tree' class from the final output.

ICA approach

For the second mapping approach, a workflow (Fig. 5) was implemented in which an NDVI image band was created from the NAIP imagery as well as a green texture band in step 1. Median filters have been used for noise reduction with high resolution imagery (e.g., Mora et al. 2010), so a 5×5 median filter was also applied in step 1 to all input bands; these filtered bands were used as inputs into the ICA data reduction step (step 2). At this point, the ICA output bands were inspected (step 2b) to determine if useful information was contained. Although it was rare, there were cases where ICA components contained no information and appeared as a blank image to the interpreter. These particular bands were removed from further processing. Next, the ICA bands were clustered using ISODATA in step 3 into 20 classes and a Maximum Likelihood Classifier was used to assign the clusters into a class. An interpreter then examined the 20 classes in conjunction with the original NAIP imagery and selected those classes that best represented tree cover (step 4b). Once the class labels (i.e., tree and no-tree) were assigned, a minimum mapping unit (MMU) of 20 pixels, or 20 m^2, was applied in step 5. This particular MMU was chosen because it represented a conservative minimum size for a single tree crown. Similar to the OBIA approach, the post-processing procedures in step 5 included mosaicing the classified output tiles together, clipping the compiled output to the county boundary, and converting the final raster to vector format using the same software. Again, the total area of tree cover was obtained from the county-level classified output. While steps 2b and 4b required human intervention, all other steps are fully automated, and batch processing was used for all 49 image tiles in the study area.

Accuracy assessment

Three different accuracy assessments were conducted in this study: nonsite-specific, site-specific, and a targeted

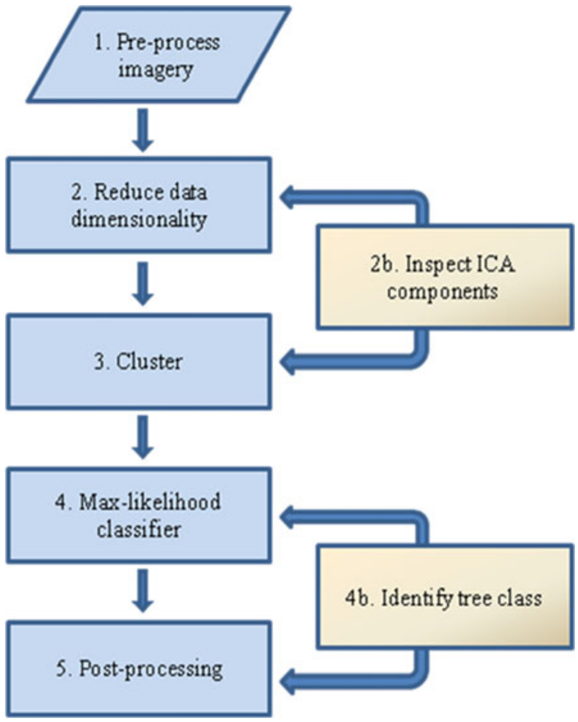


Fig. 5 Unsupervised pixel-based classification workflow for classifying NAIP imagery into tree and no-tree classes. Manual steps (*2b and 4b*) are indicated in tan, while all other steps are fully automated and can be batch processed for many images

assessment. Because the fundamental goal of the study was to obtain county-level estimates of tree-covered area and then compare those estimates to the sample-based FIA estimate of forest land area, we began with a nonsite-specific, area-based accuracy assessment. Area-based assessments are typically used to determine map accuracy by first aggregating units (pixels or image objects) to a larger area (Lunetta and Lyon 2004). While area-based assessments have inherent drawbacks (e.g., Congalton 1991), the approach met the evaluation objective of the study. The area-based assessment consisted of a cluster sample framework and heads-up digitizing to estimate the total area of tree cover across the county. Cluster sampling allowed us to sample/delineate tree cover within smaller units, or blocks, placed throughout the county rather than digitizing all tree cover, which would be very time-intensive and expensive.

In order to supplement the area-based assessment with spatially explicit information about map accuracy, we conducted site-specific and targeted assessments of the OBIA and ICA classification results as well. The site-specific accuracy assessment was employed to evaluate the locational accuracy of the two thematic classes (tree and no-tree) compared to the reference data. This type of assessment is important because it considers the location of each class, not only the total area (Jensen 1996). Within the targeted assessment, a variety of landscape pattern metrics were compared across three different landscape types within the Steele County study area: agricultural, riparian, and urban. Because the spatial pattern of tree cover in the landscapes relates to ecosystem processes, it was appropriate to examine the consistency of metrics derived from the ICA and OBIA outputs that were used to describe the spatial arrangement of tree cover.

Area-based accuracy assessment

The area-based accuracy assessment was designed to determine how well the OBIA and ICA methods performed with regard to correctly estimating the proportion of tree cover in the county. Specifically, a cluster sample was employed for the study area that used equal-sized grids (1 km^2) with centers separated by a distance of 3 km, which resulted in a total of 108 grids (Fig. 6). For each grid square, a trained photo interpreter used heads-up digitizing methodology to delineate tree cover. An estimate of the proportion of tree cover in the county was then calculated by

$$\widehat{p} = \frac{1}{n}\sum_{i=1}^{n} p_i$$

where n is the total number of grid squares in the sample and p_i is the proportion of tree cover for the ith grid square (adapted from Thompson 2002).

The standard error is given by

$$\mathrm{SE}(\widehat{\mathrm{p}}) = \sqrt{\frac{\mathrm{s}^2}{\mathrm{n}}\left(1-\frac{\mathrm{n}}{\mathrm{N}}\right)}$$

Where N is the number of square kilometers in the study area and s^2, the sample standard deviation is given by

$$s^2 = \frac{1}{n-1}\sum_{i=1}^{n}\left(p_i-\widehat{p}\right)^2$$

The county-level proportion estimate of tree cover is easily converted to an areal unit by multiplying the estimate by the total area of the county.

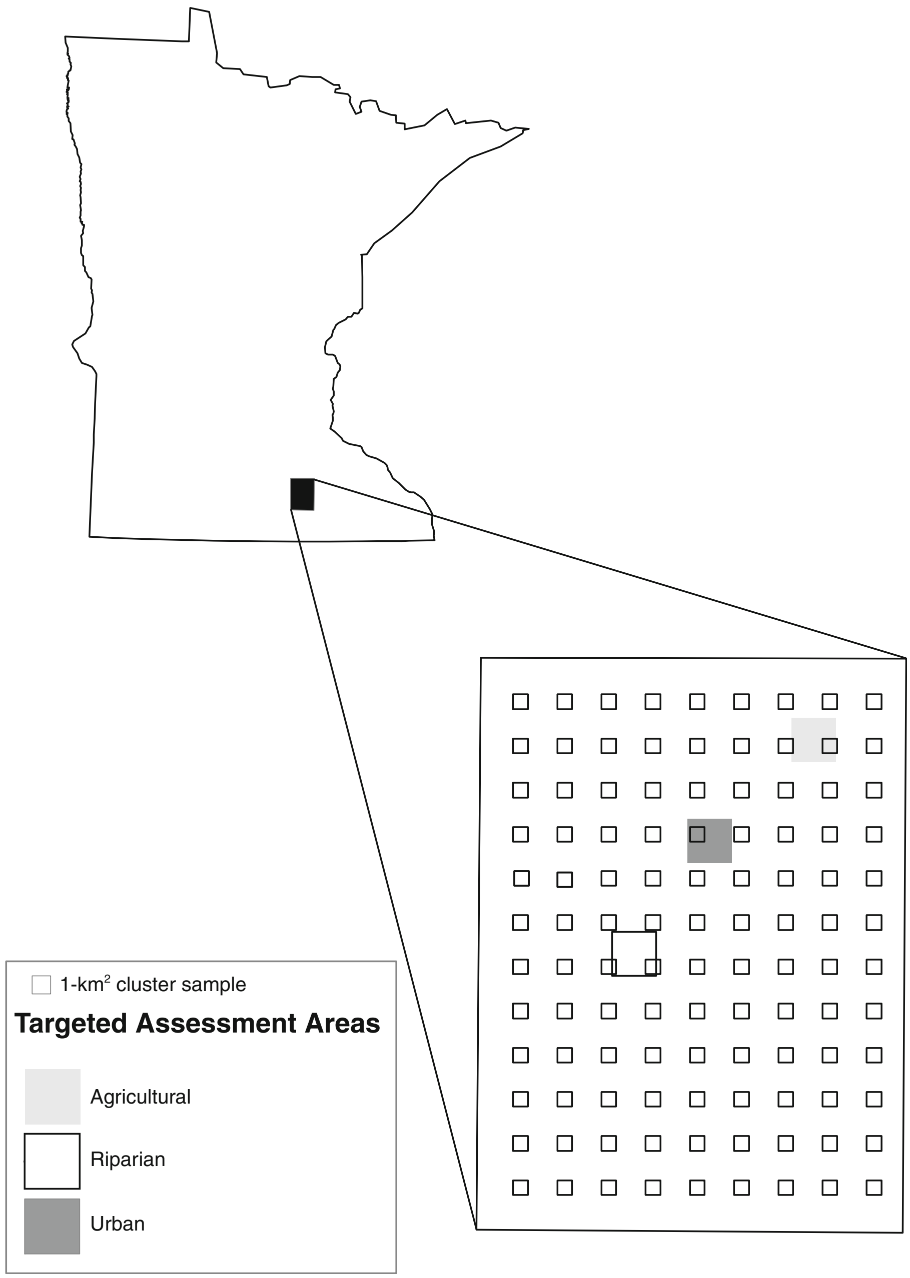


Fig. 6 Cluster sample design of 1 × 1 km blocks at 3 km intervals for the area-based assessment and location of targeted landscape assessment types (agricultural, riparian, and urban)

Site-specific accuracy assessment

Site-specific accuracy assessments were used to directly compare the classified outputs derived from the ICA and OBIA approaches to the reference data, and the accuracy of each approach was represented in an error matrix. This type of accuracy assessment is more complete than a nonsite-specific assessment because it accounts for the locational accuracy of the classified output and not only the total area.

Collecting unbiased reference data to which the classified output is compared is an important step in site-specific accuracy assessments. To accomplish this, we used stratified random sampling to select 50 samples from each stratum (i.e., the tree and no-tree classes) to ensure that both were adequately represented in the accuracy assessment (Congalton 1991). Using the high-resolution NAIP imagery as the reference data source, a trained photo interpreter labeled each sample as 'tree' or 'no-tree' and these were compared to the output classification derived from the ICA and OBIA approaches. The agreement/disagreement results were summarized in error matrices and descriptive statistics including producer's accuracy (measure of omission error), user's accuracy (measure of commission error), and overall accuracy were calculated to describe the accuracy of each thematic class produced by both classification methods.

Targeted assessment

Tree cover in the three different types of landscapes was delineated into patches using heads-up digitizing to facilitate a more detailed comparison of the classification results between the OBIA and ICA methods. Grid squares (3×3 km) were placed in a riparian area, an agricultural area with windbreaks, and in an urban setting (Fig. 6). For each of these areas, selected landscape metrics were calculated using the Patch Analyst Extension in ArcMap™ and are listed in Table 2. The targeted assessment further characterized how each approach performed in characterizing tree cover in different landscape types and addresses the questions: (1) is each classification approach equally applicable in all landscapes? And, (2) how do the approaches perform in terms of producing spatially accurate information in the various landscapes?

Area, number of patches, average patch size, median patch size, and patch density metrics are standard measures in landscape-level analyses that describe the amount and spatial arrangement of tree cover. For example, a large number of patches, a small average patch size, and a high patch density indicate that tree cover in a landscape is fragmented, occurring as many small, separate patches. Mean perimeter/area ratio is a measure used to describe the average patch shape in the landscape. The mean is calculated by summing the perimeter/area ratio of each patch and dividing by the total number of patches. A higher mean perimeter/area ratio indicates that, on average, the patches are more complex and irregular in shape. While perimeter/area ratio is a common and simple way to indicate shape, it is influenced by the size of the patch. Mean patch fractal dimension, however, allows patches to be weighted by size to help correct this problem; a value close to 1 indicates that patches have simple boundaries regardless of size whereas a value near 2 means that the patch shapes are more complex across various patch sizes (McGarigal and Marks 1995).

Results

Tree-covered area

Total tree-covered area results from the three methods are presented in Table 1. The area of tree cover found using the ICA approach was very similar (9 % difference) to the estimate obtained from the heads-up digitizing in the cluster sample while the result from the OBIA approach was substantially higher (53 % difference). In comparison, the 2010 FIA estimate of forest land for the study area is much smaller (72 % difference from the cluster sample) than all other estimates of total tree cover.

Table 1 Estimates of tree-covered area in Steele County, MN using three methods

	PI	OBIA	ICA	FIA estimate
Area of tree cover (hectares)	5,650	9,760	5,180	2,670
Proportion tree cover	0.051	0.088	0.047	0.017
Standard error	0.0038	–[a]	–[a]	0.57

Tree cover was delineated by a human photo interpreter (PI) using heads-up digitizing, semi-automated object-based image analysis (OBIA), and unsupervised pixel-based classification (ICA) approaches. Forest Inventory and Analysis (FIA) estimates of forest land were used as a comparison

[a] The OBIA and ICA methods are census approaches while the PI and FIA methods are sample based

Table 2 Comparison of landscape metrics from a targeted assessment of tree cover in agricultural, riparian, and urban landscapes (each 3×3 km) in Steele County, MN, using three methods

Metric	Agricultural			Riparian			Urban		
	PI	OBIA	ICA	PI	OBIA	ICA	PI	OBIA	ICA
Tree-covered area (ha)	20.5	27.4	14.6	100.7	129.1	77.8	237.5	301.2	176.8
Number of patches	93	49	919	105	81	1,880	3,967	169	12,535
Average patch size (ha)	0.22	0.56	0.02	0.96	1.59	0.04	0.06	1.78	0.01
Median patch size (ha)	0.05	0.25	0.005	0.03	0.29	0.004	0.01	0.45	0.004
Standard deviation of patch size (ha)	0.43	0.67	0.07	5.82	8.22	0.90	0.51	3.98	0.09
Patch density (patches/km^2)	10	5	102	12	9	209	441	19	1,393
Mean perimeter/area ratio	2,695	2,149	10,622	3,116	2,576	11,740	4,611	2,526	12,628
Mean patch fractal dimension	1.53	1.57	1.96	1.55	1.61	1.98	1.63	1.56	1.99

Tree cover was delineated by a human photo interpreter (PI) using heads-up digitizing, semi-automated object-based image analysis (OBIA), and unsupervised pixel-based classification (ICA) approaches

Site-specific accuracy assessment

The results of the site-specific accuracy assessments indicate that both classification approaches produced reliable maps of tree cover versus no-tree cover. The overall accuracy of each map was high, 88% and 95% for the ICA and OBIA outputs, respectively. The producer's and user's accuracies for the classification output derived from the OBIA approach were above 90 % for both classes. The accuracy assessment results for the ICA approach were more varied. While the user's accuracy for the 'tree' class was 100 %, the producer's accuracy was only 76 %. For the 'no-tree' class, user's accuracy was 81 % and the producer's accuracy was 100 %.

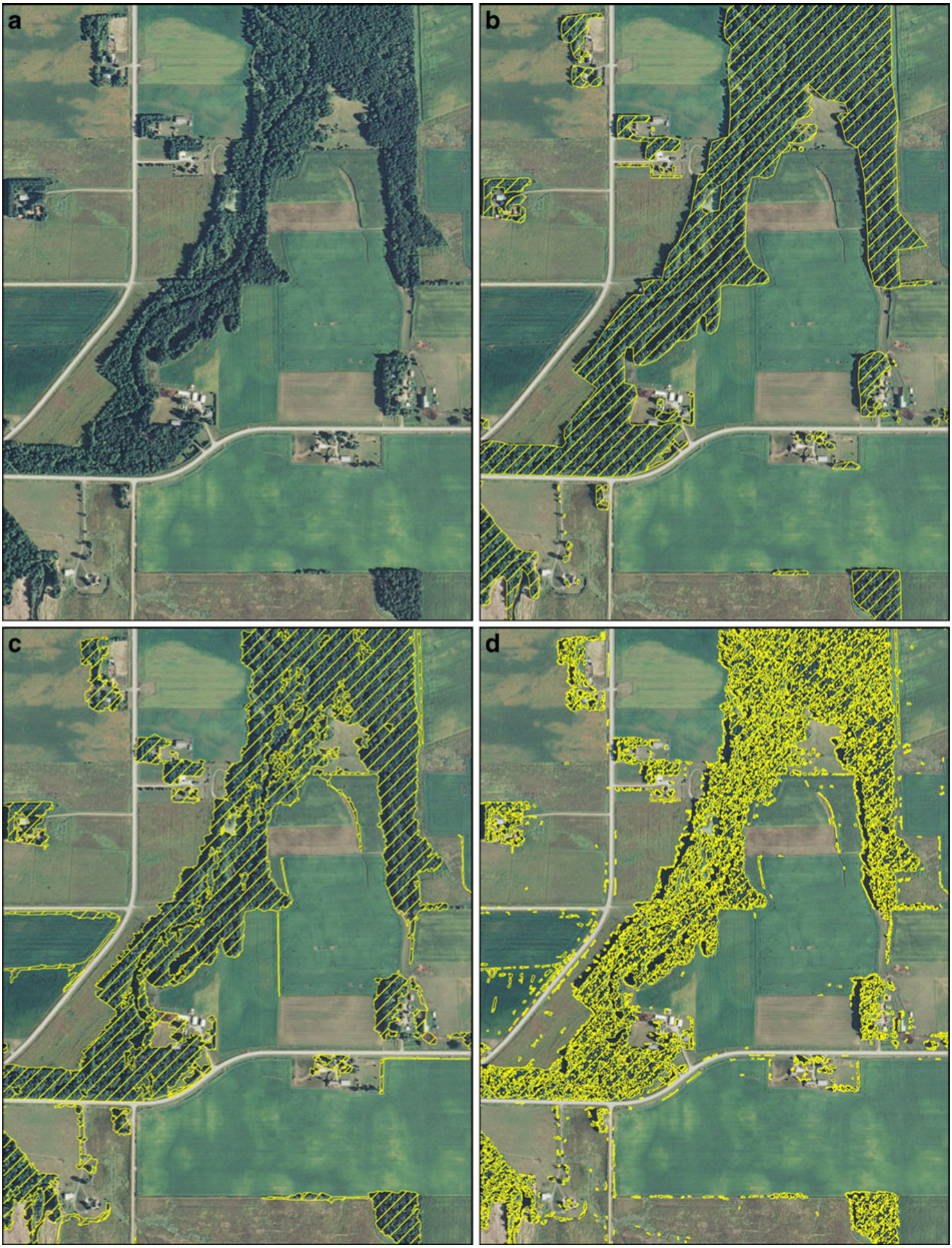
Tree cover patch metrics

The three approaches performed differently in providing estimates of tree cover patch metrics (Table 2). The ICA approach resulted in a smaller tree-covered area relative to the heads-up digitized approach while the OBIA method resulted in more tree-covered area for all three landscapes. The ICA method also tended to produce many smaller patches of tree cover in all landscapes compared to the other two approaches. This is illustrated by the substantially higher numbers of patches, smaller average and median patch sizes, and higher patch densities calculated from the ICA output map. Regarding patch shape, the ICA approach produced patches with more complex perimeters, as indicated by mean patch fractal dimension values close to 2, in all the target landscape types.

In the agricultural and riparian landscapes, the metric results derived from the OBIA output were consistently more similar to the PI results than those obtained from the ICA output. Mean perimeter/area ratio and mean patch fractal dimension metric results from the PI and OBIA methods are comparable, indicating that the two approaches tended to produce similarly shaped patches of tree cover. In contrast, the ICA approach created patches with much more complex shapes, e.g., often small and blocky in shape with a high number of edges per patch. Figures 7a through d show an example from the riparian target area (Fig. 7a) comparing the output from heads-up digitizing (Fig. 7b), and the OBIA (Fig. 7c) and ICA (Fig. 7d) approaches.

The metric results for the urban landscape varied widely among the three methods. In contrast to the ICA approach, the OBIA method produced far fewer and larger patches: 169 compared to more than 12,000, with an average size of 1.78 ha versus 0.01 ha. The only OBIA metrics that were somewhat similar to the PI results were tree-covered area and mean patch fractal dimension. The PI and ICA methods, however,

Fig. 7 a–**d** Example of the riparian landscape type and comparisons of delineation of tree cover using three methods in Steele County, MN. Unclassified NAIP image (**a**), tree cover assessed by a human photo interpreter using heads-up digitizing (**b**), semi-automated object-based image analysis (OBIA) (**c**) and unsupervised pixel-based classification (ICA) (**d**) approaches


a
b
c
d

produced many smaller patches that were more similar in average size compared to patches created by the OBIA approach. Again, the ICA approach produced the most complex-shaped patches of tree cover.

Discussion

Tree cover in nonforest settings is a sparse yet important resource. The lack of current inventory and monitoring programs of ToF is a concern; however, obtaining accurate information about its extent and location is challenging. Additional ground-based data collection as part of an NFI is relatively expensive and does not provide detailed spatial information that can be used in other research and applications, such as determining ecosystem function. Commonly used and widely available land cover datasets are acquired at spatial resolutions that are too coarse to detect small patches and narrow bands of tree cover and specialized higher resolution imagery can be costly. In order to find a potential solution to these issues, two remote sensing-based approaches, OBIA and ICA, were examined for mapping all tree cover in an agricultural landscape using freely available, very high-resolution (1 m) aerial imagery.

When determining the total area of tree cover for Steele County, Minnesota, the ICA approach produced an estimate similar to that found from heads-up digitizing in the cluster sample (5,180 ha versus 5,650 ha respectively). The OBIA estimate, on the other hand, was much higher (9,760 ha), and all tree cover estimates are substantially higher than the FIA estimate of forest land (2,670 ha). The findings reinforce what other authors have reported, that the definition of forest land excludes a significant portion of tree cover in agricultural landscapes from NFIs. In this case, the total area of tree cover in Steele County is potentially three times as much as the forest land area estimate would indicate if we consider the PI estimate to be the most accurate reference or standard. Examination of the OBIA and ICA outputs indicate that both methods struggle with shadows and grassy vegetation along roadways and in ditches, and sometimes erroneously label these areas as tree cover. The speckled appearance of the ICA output is due to the occurrence of many tiny, disjunct patches and is evidenced by the results shown in Table 2 (e.g., large numbers of patches with very small average patch sizes) and Fig. 7d. The OBIA approach alleviated this problem by aggregating pixels into larger image objects and prevented the formation of such extraneous tiny patches. However, this contributed to the overestimation of tree-covered area when image objects were misclassified. For example, inspection of the OBIA output revealed that some farm fields and wetland areas were misclassified and resulted in additional large patches of tree cover. Additional research and development of the procedures will help correct the shortcomings.

While the accuracy of the OBIA and ICA methods can be improved, they do provide an advantage over the cluster sample with regard to providing more spatial detail. The arrangement of tree cover and its proximity to other landscape features provides information about ecosystem function. For example, tree cover arranged in winding, narrow strips adjacent to streams serve as riparian buffers. Trees planted in rectangular or L-shaped blocks around buildings offer protection from the weather and increase energy efficiency in those structures while linear strips of trees along field edges provide shelter from the wind and help prevent soil erosion. If a spatial database of tree cover was constructed using the OBIA or ICA approaches, ecosystem function information could be extracted, and that is not an option readily achievable using data from a PI cluster sample.

The targeted assessment provides additional information about the ability of each method to characterize the spatial arrangement of tree cover compared to patches delineated by a human photo interpreter. In this case, it is easy to see that the pixel-based approach (ICA) leads to an extremely high estimate of the number of patches and correspondingly low average patch size. The OBIA approach is much better at mimicking how a human interpreter groups trees into patches, thus producing a result that most closely resembles that from the PI approach. While many authors focus on the processing efficiency of OBIA methods, the generally better appearance of output maps, and export options (e.g., Benz et al. 2004), this study points to another potential advantage over pixel-based approaches: the ability to produce better patch-based metrics for describing spatial pattern. However, when conducting ecological studies that use landscape metrics, it is important to remember that the spatial resolution of the imagery used in the metric calculations will affect the results. The principal investigator of the study should carefully select metrics and imagery that are appropriate for their research objectives.

Examination of the results in the urban target area clearly indicates that this type of landscape is extremely complex and it is difficult to accurately delineate tree cover using either of the remote sensing-based approaches. The OBIA method had a tendency to group together individual tree crowns that were in close proximity to each other while a human interpreter was able to delineate each crown separately. In contrast, the ICA approach produced output that was very speckled in appearance and often misclassified shadows around buildings and tree crown edges as tree cover. The highly variable results of the metrics from the three approaches led us to conclude that a new, separate classification model needs to be developed for urban landscapes and that future work will focus strictly on rural settings. Furthermore, the similarity of the results between the PI and OBIA approaches in the agricultural and riparian target areas is reassuring since these are the landscape types in which we are ultimately interested in for natural resource inventory and monitoring purposes. However, it is very likely that the OBIA approach will need to be modified in terms of adjusting the user-defined settings in the eCognition software when using other imagery and/or when moving to a much different geographic area in order to create meaningful image objects.

The need was highlighted for methodologies that can be accurately and efficiently applied to mapping tree cover in areas where the resource is not inventoried with satisfactory results. The workflows developed for both the OBIA and ICA approaches are at least partially automatable, using either programming scripts or built-in batch processing capability of the software used, and do not require the use of expensive imagery. As such, either method represents a viable approach to mapping tree cover over a broad spatial extent and could serve to supplement NFIs. The utility was demonstrated on a county with more than 100,000 ha of land area and the results were compared using three different accuracy assessment approaches. Remote sensing-based approaches, such as OBIA or ICA, represent a step forward from traditional sample-based PI methods because of the additional spatial information they provide. In addition, NAIP imagery is available on a periodic schedule so it would be possible to monitor these tree resources over time. Because the OBIA approach produced classification results that were more accurate in terms of spatial location and also provided more reasonable information about the spatial pattern of tree cover, it is the better choice.

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