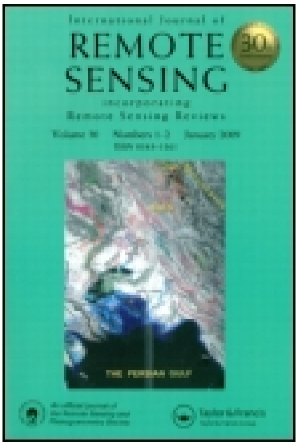

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Does spatial resolution matter? A multi-scale comparison of object-based and pixel-based methods for detecting change associated with gas well drilling operations

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Does spatial resolution matter? A multi-scale comparison of object-based and pixel-based methods for detecting change associated with gas well drilling operations

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An implicit assumption of the geographic object-based image analysis (GEOBIA) literature is that GEOBIA is more accurate than pixel-based methods for high spatial resolution image classification, but that the benefits of using GEOBIA are likely to be lower when moderate resolution data are employed. This study investigates this assumption within the context of a case study of mapping forest clearings associated with drilling for natural gas. The forest clearings varied from 0.2 to 9.2 ha, with an average size of 0.9 ha. National Aerial Imagery Program data from 2004 to 2010, with 1 m pixel size, were resampled through pixel aggregation to generate imagery with 2, 5, 15, and 30 m pixel sizes. The imagery for each date and at each of the five spatial resolutions was classified into Forest and Non-forest classes, using both maximum likelihood and GEOBIA. Change maps were generated through overlay of the classified images. Accuracy evaluation was carried out using a random sampling approach. The 1 m GEOBIA classification was found to be significantly more accurate than the GEOBIA and per-pixel classifications with either 15 or 30 m resolution. However, at any one particular pixel size (e.g. 1 m), the pixel-based classification was not statistically different from the GEOBIA classification. In addition, for the specific class of forest clearings, accuracy varied with the spatial resolution of the imagery. As the pixel size coarsened from 1 to 30 m, accuracy for the per-pixel method increased from 59% to 80%, but decreased from 71% to 58% for the GEOBIA classification. In summary, for studying the impact of forest clearing associated with gas extraction, GEOBIA is more accurate than pixel-based methods, but only at the very finest resolution of 1 m. For coarser spatial resolutions, per-pixel methods are not statistically different from GEOBIA.

1. Introduction

Geographic object-based image analysis (GEOBIA, also commonly known as object-based image analysis (OBIA); Hay and Castilla 2008; Blaschke 2010) has become an increasing focus of the remote-sensing community, especially in the past decade. This rising interest in GEOBIA is usually ascribed, at least in part, to the advent of commercial fine spatial resolution (with a pixel size less than 10 m) satellite imagery (Blaschke et al. 2000; Hay and Castilla 2008). Fine spatial resolution imagery is assumed to have high local variability in pixel digital numbers (DNs). Consequently, analysis and classification that is based on

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contiguous groups of pixels, termed *image objects* (or just *objects*, for short), is assumed to be more effective than one based on individual pixels, since the objects effectively suppress this local variability in the final map product (Johansen et al. 2010; Kim et al. 2011; Malinverni et al. 2011). In moderate spatial resolution images (10–100 m), the individual pixels are expected to contain multiple ground objects, and therefore GEOBIA is regarded as less useful for such images (Blaschke 2010). Thus, for example, Giner and Rogan (2012) used GEOBIA for high spatial resolution aerial imagery, but pixel unmixing methods for Landsat images. Nevertheless, a number of studies have found GEOBIA-based methods effective for classification of moderate resolution imagery (e.g. Matinfar et al. 2007; Gamanya, De Maeyer, and De Dapper 2009). Notably, however, comparisons between pixel- and object-based methods using fine resolution imagery generally find object-based methods more accurate (e.g. Platt and Rapoza 2008; Pringle et al. 2009), but at moderate resolutions the relative benefits are less clear. For example, Robertson and King (2011), using 30 m Landsat Thematic Mapper (TM) data, found no significant difference between the two approaches, although when the classifications were used for change detection, they found some evidence that object-based methods were more accurate. Dorren, Maier, and Seijmonsbergen (2003) found that pixel-based methods of forest classification were more accurate statistically, but they also noted that local foresters evaluated the object-based maps as being a better representation of the change.

The focus on high spatial resolution as a driver of GEOBIA development, and the ambiguous findings in previous studies regarding GEOBIA with moderate resolution imagery, raises the question whether GEOBIA is inherently more accurate at fine spatial resolutions than moderate resolutions, and how both pixel-based and object-based methods compare in relative accuracy as a function of spatial resolution. (For simplicity sake, we use ‘scale’ to refer to spatial resolution, although it is important to bear in mind that image scale has additional components (Warner, Nellis, and Foody 2009b).) The issues of scale and GEOBIA classification are addressed in this article within the context of the identification of recent, rapid, and spatially extensive land-cover change associated with forest clearing for natural gas well drilling sites in the central Appalachian Plateaus physiographic province, USA (Fenneman 1917) (Figure 1). Although the clearings within the study site are relatively small (averaging 0.9 ha, with a range in size from 0.2 to 9.2 ha), the large number and dispersed locations suggest that the cumulative effect, especially in terms of forest fragmentation, may be great. The primary data set was aerial imagery with a pixel size of 1 m, from which additional spatial scales from 2 to 30 m were synthesized. Many papers have examined the role of the scale of the objects in GEOBIA (e.g. Kim, Madden, and Warner 2009; Liu and Xia 2010; Drăguţ and Eisank 2011), but to our knowledge this is the first paper to methodically examine the effect of the scale of the pixels used to generate the objects.

2. GEOBIA, classification, and change detection

Traditional, aspatial classification methods analyse remotely sensed imagery on a pixel-by-pixel basis, irrespective of the decisions made for neighbouring pixels (Jensen et al. 2009). Maximum likelihood classification is one of the most common pixel-based classification methods because of its ‘simplicity and robustness’ (Platt and Goetz 2004, 816). Maximum likelihood classification assigns pixels to a land-cover class based upon the maximum probability a pixel belongs to one of a number of classes provided by the user as training samples. Although pixel-based classifications such as maximum likelihood classification are often criticized for the ‘salt and pepper effect’, which is a consequence of

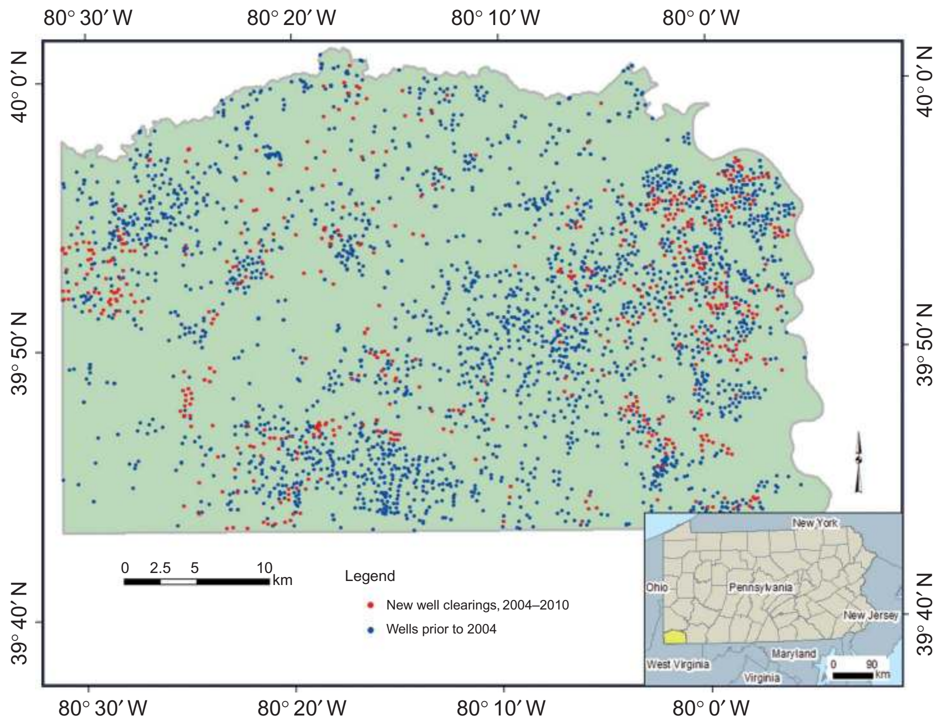

Figure 1. Map of the study area showing active oil and gas well permit locations in Greene County, Pennsylvania, USA.

Note: The inset map shows Greene County's location in southwestern Pennsylvania.

classifying each pixel independently, this high spatial frequency variation can, if required, be suppressed. A simple way to increase autocorrelation in the final product is to apply a post-classification smoothing, such as by applying a majority filter to the classification, or a filter that replaces clumps smaller than a threshold by the surrounding classes (Townsend 1986; Newman, Mclaren, and Wilson 2011). However, it is important that users are made aware that smoothing filters have been applied to a classification, since such filters have the effect of changing the minimum mapping unit of the resulting map.

Compared to pixel-based methods, GEOBIA offers the benefit of classifying an entire group of pixels as a unit, using, for example, both average and variation in the spectral DNs. In addition, GEOBIA offers the potential to exploit geographical information system (GIS) functionality, such as the incorporation of the spatial context or object shape in the classification (Blaschke 2010).

The first step in object-based classification using the software package eCognition (Trimble, Sunnyvale, California) is to segment the image into objects that are assumed to have real-world meaning (Baatz and Schäpe 2000). The eCognition multiresolution segmentation algorithm has three main user-set parameters: scale, shape, and compactness (Trimble 2011). The relative magnitude of the scale value determines the size of the segmented objects (Liu and Xia 2010; Kim et al. 2011). The shape parameter defines the relative weight assigned to polygon shape versus colour, a term used to describe spectral homogeneity. Compactness values determine the balance between the object form and edge length (Baatz and Schäpe 2000). After segmentation, the derived objects may be classified using textural, spectral, and other properties of the object specified by the user (Trimble 2011). Two approaches that are commonly used with eCognition are the membership function classifier and the nearest neighbour classifier. The membership function classifier requires an expert to create rules for classifying objects, whereas the nearest neighbour classifier requires training objects for each class (Myint et al. 2011).

Change detection using remotely sensed imagery has proved to be useful in a wide range of natural resource extraction studies, especially in surface mining (e.g. Townsend et al. 2009) and logging (e.g. Franklin et al. 2002). As with image classification, change detection methods include both pixel-based and GEOBIA methods (Warner, Almutairi, and Lee 2009a). A common pixel-based method for observing land-cover change is post-classification change detection. This method of change detection uses independently classified thematic maps followed by a GIS overlay to assess land-cover change between the classifications (Jensen 2005). Post-classification change detection is regarded as one of the simplest approaches to change detection studies because atmospheric correction is not required (Warner, Almutairi, and Lee 2009a). However, one of the major criticisms of this approach is that the error of the change analysis can be, at least in the worst case, the product of errors of the independent classifications (Singh 1989; van Oort 2007). Furthermore, as with all pixel-based methods, a precise co-registration between the images of different dates is essential (Dai and Khorram 1998).

Whereas pixel-based change detection is limited to change of individual pixels, GEOBIA change detection has the potential to address some of the challenges of traditional methods. Because it produces homogeneous objects, GEOBIA change detection does not suffer from spatially uncorrelated salt-and-pepper noise in the change products. On the other hand, GEOBIA change detection is very sensitive to the locations of the delineated object boundaries. Slight changes in object delineation between the different dates due to differences in image co-registration, sun-angle, or even just natural variation in image DNs will result in spurious identification of change along the object boundaries (Gamanya, De Maeyer, and De Dapper 2009).

Post-classification GEOBIA change detection is based upon three steps. First, the images are segmented into image objects (Blaschke 2010). These objects are then classified into land-cover categories (Gamanya, De Maeyer, and De Dapper 2009; Myint et al. 2011), and then in the final stage the change is mapped. Ideally, change would be identified on an object basis (Gamanya, De Maeyer, and De Dapper 2009; Chen et al. 2012). A simple alternative to the complexities of an object-based approach is to apply a raster GIS overlay of the GEOBIA classifications, ignoring the object relationships. The disadvantage of this approach is that changes to specific objects are lost. However, in cases where individual objects are not of interest, this strategy provides an effective method for assessing land-cover change.

3. Study area and data

The study area for this research is Greene County, located in the southwestern corner of Pennsylvania and bordered on the west and south by West Virginia (Figure 1). The county covers approximately 1500 km^2 and has a population of 40,672, with nearly 70% of the population living in areas designated as rural (United States Census Bureau 2000). Technological advancements in natural gas development, including hydraulic fracturing and horizontal drilling, have led to a rapid increase in the rate of natural gas exploration within organic-rich shale. The Marcellus Shale formation, which underlies all of Greene County, has been a recent target of intense energy exploration. In this research, we compare object-based and pixel-based classification methods for overall accuracy of land-cover

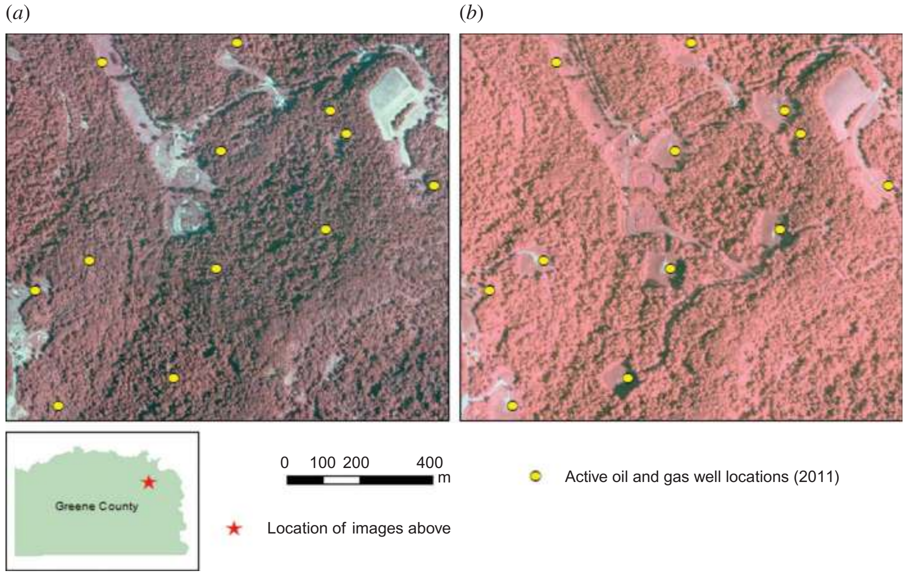

Figure 2. Standard false colour infrared National Agricultural Imagery Program (NAIP) images of well locations in the forested area near Jefferson, Pennsylvania (centred at 39° 55′ 18″ 80° 2′ 31″). (*a*) 2004 and (*b*) 2010. Notice increased fragmentation following the placement of well clearings in the 2010 imagery.

change map products associated with well drilling, as well as for identifying new well clearings within the study area between two image dates (e.g. Figure 2). Through the simulation of images of different spatial scales, this research has implications for change detection studies using sensors that range from fine resolution (e.g. QuickBird) to moderate resolution (e.g. Landsat TM). This research thus serves as a foundation for further investigation into natural gas development and its impacts on local ecosystems, and may be tailored to community-specific habitat evaluations in the future.

The primary image data consist of the United States Department of Agriculture (USDA) National Aerial Imagery Program (NAIP) imagery, with 1 m pixels. Two dates of NAIP imagery of Greene County were purchased from the USDA Aerial Photography Field Office (APFO, http://www.apfo.usda.gov/), one set acquired in 2004 and another in 2010. These two dates were selected to capture the beginning (2004) and a period close to the peak (2010) of the boom in Marcellus exploration. The 2004 images have three spectral bands in the green, red, and near infrared, and were acquired during the leaf-on period, between 20 June 2004 and 3 September 2004 (with the exception of one quarter quadrangle on the edge of the study area, which was collected on 7 October 2004). The 2010 images were acquired with blue, green, red, and near-infrared bands, and were collected between 18 June 2010 and 2 September 2010. An ancillary point data set containing all active oil and gas well permit locations available from the Pennsylvania Spatial Data Access (PASDA, http://www.pasda.psu.edu/default.asp) was used as a reference for identifying new well locations for the period between the 2004 and 2010 image acquisitions.

4. Methods

4.1. Preprocessing

The quarter quadrangle NAIP image tiles of Greene County were mosaicked using Erdas Imagine 2011 (ERDAS 2011) by applying a histogram match of the 300 m overlap areas

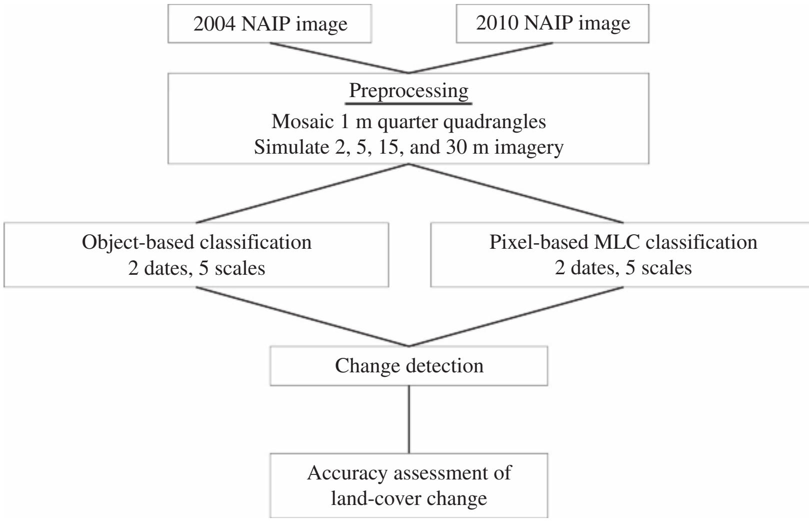

Figure 3. Research flow chart showing the main steps in methods and analysis.

for normalization (Figure 3). Although the majority of the tiles appear to be matched well with this procedure, it was not possible to remove minor differences between a few tiles due to differences in shadowing, vegetation phenology, and other image artefacts. Next, the 1 m imagery was resampled to coarser spatial resolutions through averaging of adjacent pixels to produce four additional images at 2, 5, 15, and 30 m (Figure 3). The upper limit of 30 m was chosen to coincide with the Landsat pixel size, and also to ensure that the pixel size was always smaller than that of the smallest well pad. The resampling approach was selected in order to ensure the maximum spectral and phenological consistency between the images of the various scales, which would be hard to achieve if images from different sensors were used (Yang and Merchant 1997). These preprocessing steps were performed using both the 2004 and 2010 imagery, to produce a total of 10 images (two dates, five scales) used in the classification and analysis.

A qualitative visual comparison through overlaying the 2004 and 2010 images suggested that although the co-registration error is mostly less than 1 m (i.e. 1 pixel), in places the error is as high as 3 m, most likely due to limitations of the data used in the orthorectification of the original photographs, such as the digital elevation model. The distribution of error appeared to be random, and attempts to reduce the error through warping one image to match the other were not successful. Further geometric co-registration was therefore not performed. Because the size of the gas well clearings is much greater than this error (see next section), and the vast majority of the images were co-registered with an error of less than 1 pixel, co-registration error was not regarded as likely to have a major impact on the results.

4.2. Land-cover classifications

A binary classification scheme using only Forest and Non-forest classes was used to classify the 2004 and 2010 images at each spatial resolution using the three spectral bands common to both data sets (green, red, and near-infrared bands). Forest was defined as patches of tree cover exceeding a minimum mapping unit (MMU) of 1800 m^2 (equivalent to the area of 1800 1 m pixels, or two 30 m pixels). Non-forest was defined as all other land-cover classes. These class definitions were used for both the 2004 and 2010 images at each of the five spatial resolutions.

Maximum likelihood classification was used for the pixel-based classification to produce thematic maps of land cover for both image dates. Maximum likelihood classification was chosen to benchmark the pixel-based methods because it is regarded as a standard approach, and is highly effective if the classes at least approximately satisfy the assumption of multivariate normality (Swain and Davis 1978; Jensen et al. 2009). To ensure that the classification results were optimal, a hierarchical approach was adopted. The two classes of interest, Forest and Non-forest, were each subdivided into multiple spectral subclasses, representing all distinct classes in the scene including buildings, paved surfaces, open grasslands, bare soil, agricultural fields, and water. For example, within the paved class, a spectral subclass of bright impervious surfaces was identified. Five to ten separate sets of training samples were then collected for each spectrally distinct subclass. These individual training samples were treated as separate spectral classes, which were merged only after classification. A thematic map was produced for each spatial resolution of the 2004 and 2010 images and then overlaid to produce a final map of land-cover change at each of the resolutions. These images were filtered using the Erdas Imagine 2011 ‘Clump’ and ‘Eliminate’ processes to remove patches less than the MMU of 1800 m^2 for all types of land-cover classes and to replace the land-cover value with the same class as the majority of the surrounding pixels (Newman, Mclaren, and Wilson 2011).

Object-based classifications were performed using eCognition Developer 8 (Trimble 2011). The multiresolution segmentation algorithm was used to segment each of the images, with a trial-and-error approach used to determine the optimal scale, shape, and compactness segmentation parameters. The final parameters chosen were 0.1 for shape, 0.5 for compactness, and scale parameters that varied as a function of pixel size: 25 for 1 and 2 m pixels, 10 for 5 m pixels, and 5 for 15 and 30 m pixels. All three spectral bands were used in the segmentation, with the near-infrared band weighted twice as much as the green and red bands because the forest class is most distinctive at these wavelengths.

Once the image segmentations were produced, rulesets were developed by testing a range of rules for classifying Forest and Non-forest objects using a trial-and-error approach. The rules included thresholds for mean brightness, standard deviation of single bands, mean values of single bands, and a normalized difference vegetation index (NDVI) ratio parameter (Tucker 1979). The same rules were used for each classification, although thresholds of the parameters were manually adjusted to produce what was qualitatively determined to be the optimal classification for each of the five scales for each of the two dates. Rasterized polygon classifications were exported from eCognition Developer 8 and overlaid to produce the map of change objects. The maps of land-cover change were then filtered using the same logical filtering methods as the pixel-based classifications to eliminate objects smaller than the MMU.

4.3. Land-cover change map accuracy assessment

Accuracy assessments were performed for the maps of land-cover change using a visual interpretation of the 1 m images as the reference data source. The number of sample points was determined using a multinomial distribution based on the number of classes (four change classes), the proportion of the largest class (approximately 60% forest), and a 95% confidence level with 7% precision (Congalton and Green 2009). The estimated necessary sample size was rounded up, and 300 randomly generated points were used for accuracy assessment of the thematic maps produced using the pixel-based maximum likelihood classification method. The same points were used for each of the land-cover change maps at the five resolutions.

Although the kappa statistic (Cohen 1960) is a common summary accuracy measure, its use in remote sensing has been increasingly questioned (e.g. Stehman and Foody 2009). Pontius and Millones (2011) propose quantity and allocation disagreement as alternative measures. Quantity disagreement is defined as the difference between the reference data and the classified data based upon mismatch of class proportions. Allocation disagreement can be considered as the difference between the classified data and the reference data due to incorrect spatial allocations of pixels in the classification. The total disagreement is the sum of the quantity and allocation disagreements (Pontius and Millones 2011).

A review of the literature by Rakshit (2012) reveals that there is no standardized method for accuracy assessment of object-based classifications. However, Congalton and Green (2009) have suggested that objects should be the sampling units of thematic accuracy assessment for maps produced using GEOBIA methods. In this research, the unit for the object-oriented accuracy polygons of assessment was the change polygon, defined by the intersection of the two underlying dates (Figure 4). The object-based method of accuracy assessment consisted of two parts. First, the points employed in the pixel-based accuracy assessment were used in eCognition Developer 8 to extract the objects from both the 2004 and 2010 classifications, which contained the randomly selected sample points. These separate sets of objects were then intersected using ArcMap 10 (ESRI, Redlands, California) and the intersection of the two objects was used as the polygons for accuracy assessment. The majority cover type of this polygon was used as the reference class, as recommended by Dorren, Maier, and Seijmonsbergen (2003). Overall accuracy of object-based maps was calculated on an area-weighted basis, in which the summed area of correctly classified objects is divided by the total area of all objects used in the assessment.

A comparison of thematic map accuracies of the final change products was performed to investigate how overall accuracy changed with spatial resolution, as well as how accuracy varied between classification methods. Uncertainty estimates were also calculated using a modified version of the equation used to determine the sample size based on binomial probability theory (Jensen 2005):

$$E = \sqrt{\frac{Z^2 pq}{N}}, \tag{1}$$

where E is the error estimate for a specified sample size, N, with accuracy p and confidence level $q = 100 - p$ (Fitzpatrick-Lins 1981). The value for Z is 2 in this equation and is an approximation of the standard normal deviate of 1.96 for the 95% two-sided confidence level. Error estimates were calculated to determine statistical differentiation of overall thematic accuracy from another.

4.4. Land-cover change of new clearings accuracy assessment

In addition to investigating how overall accuracy varies with spatial scale and classification method, we also examined how scale and classification method affect accuracy for identification of new clearings within forested areas associated with natural gas development. The gas well point data set was used to identify the wells that were not present in 2004 and were present in the 2010 imagery (i.e. the land cover went from Forest to Non-forest). Assessing land-cover change using the point data set of well locations is not straightforward, since

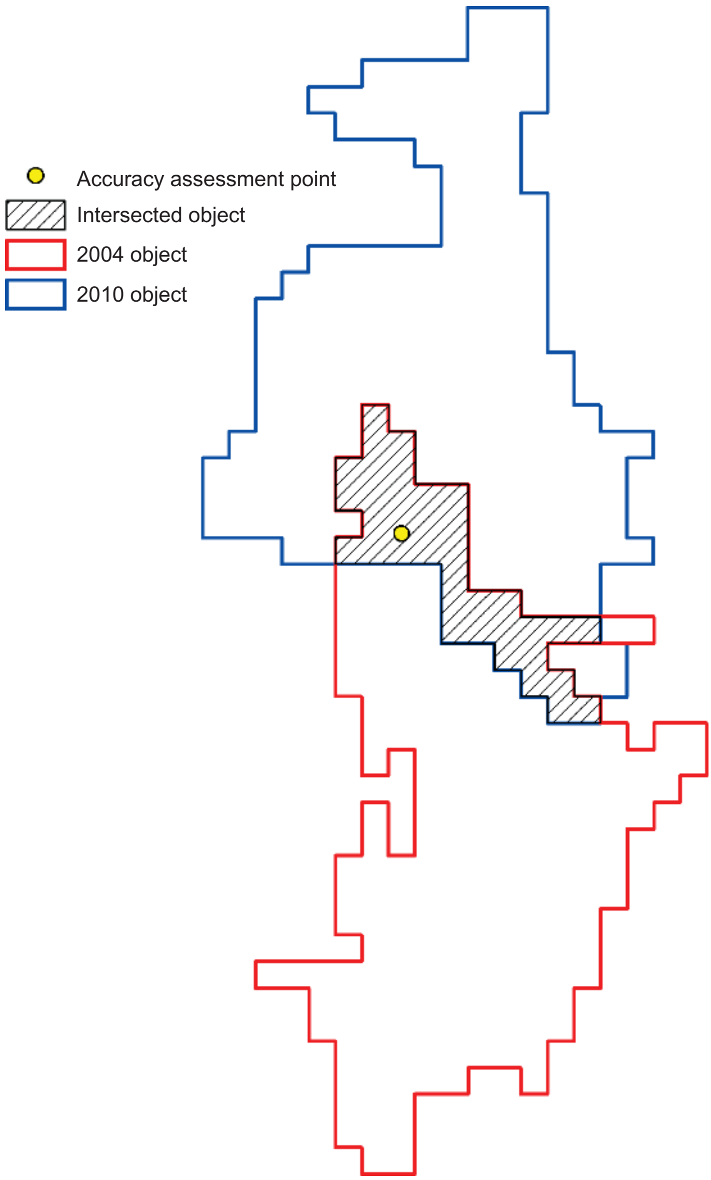

Figure 4. Example of object-based accuracy assessment polygon.

the features of interest, well clearings, comprise areas, not points. Therefore, 180 new well permit point locations were randomly selected throughout the county and the extent of each well pad clearing was manually digitized using the 1 m imagery. This manually digitized polygon included only the well clearing, and excluded access roads to the sites that were sometimes visible. All polygons included in the accuracy assessment were greater than the MMU of 1800 m^2.

The well clearing polygons were then converted to raster files, one for each of the five spatial resolutions studied, and the land-cover classes mapped in the change analysis within each clearing were summarized using the land-cover change maps of both classification methods for each of the respective spatial resolutions. The total area of each class from the sample of 180 clearings was tabulated and the proportion of correctly identified land-cover change within each polygon was summarized. Each polygon well clearing was assumed to represent the 'Forest to non-forest' change class and a percentage of correctly identified change was calculated to provide a measure of how well each classification method and spatial resolution combination identified land-cover change of well clearings.

5. Results and discussion

5.1. Land-cover classification comparison

For the small area shown in Figure 5, the well clearings are apparent in the pixel-based maps at each of the spatial resolutions as either cyan areas (new clearings with exposed soil or stone) or relatively smooth-textured, pale pink areas (grass-covered clearings). However, the full extent of the well clearings for this area is not accurately reflected in any of the change maps (Figures 5(*c*) and (*d*)). Differentiation between forest and some non-forest cover types appears to be more accurate at pixel sizes of 1, 2, and 5 m than at 15 and 30 m. For example, the clearing in the southeast portion of the 2004 and 2010 sample images (indicated by the letter 'A' in Figure 5(*a*)) is identified mostly as 'Unchanged non-forest' (black in the change classification) at all resolutions of the per-pixel change maps, but the clearing on the far west of the images ('B' in Figure 5(*a*)) is identified as 'Forest to non-forest' (red) at the three finer spatial resolutions, and is a mixture between 'Unchanged non-forest' and 'Non-forest to forest' (pale green) in the 15 and 30 m change maps. The

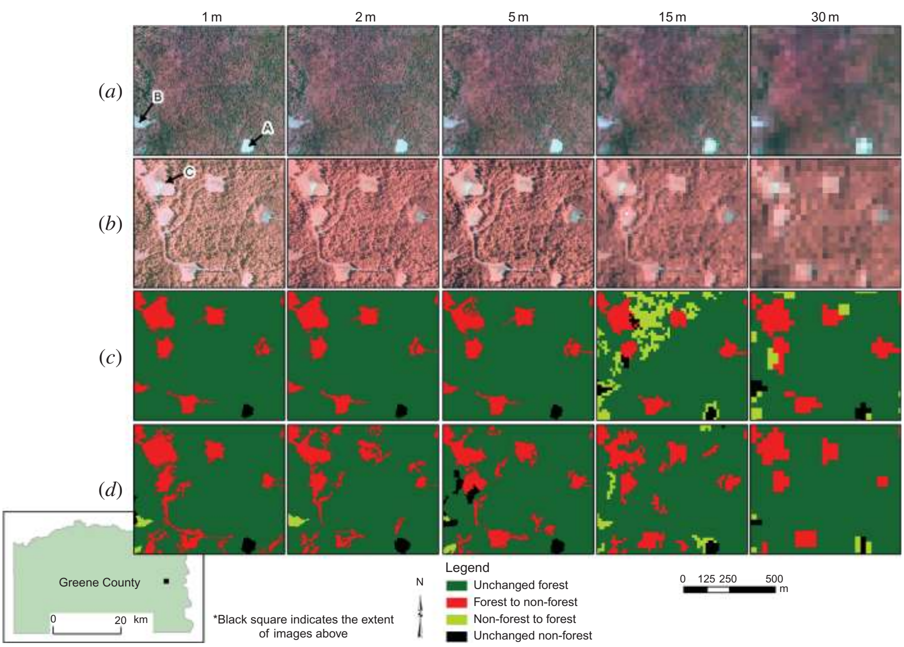

Figure 5. Example images and change maps at five spatial resolutions (1–30 m): (*a*) 2004 standard false colour composite of the original image; (*b*) 2010 standard false colour composite; (*c*) pixel-based change map; (*d*) object-based change map. Note that both of the change maps have been filtered to eliminate all land-cover patches less than 1800 m^2.

'Non-forest to forest class' is primarily in areas that were in fact forest in both images and did not change over the time period. This indicates that the areas were misclassified in the 2004 image but were correctly classified in the 2010 image. Visual inspection of the maps of land-cover change produced using the pixel-based maximum likelihood classification method indicates a slight variation in the classifications as the spatial resolution changes, although the well clearings are identified reasonably well at all spatial resolutions.

The GEOBIA-based classification identified the disturbed forest associated with each well clearing, although the extent of the clearings is not as evident for some clearings as it was in the pixel-based classifications (Figure 5(*d*)). For example, the well clearing in the northwest portion of the sample figures ('C' in Figure 5(*b*)) shows a new clearing in 2010, but the 2, 5, and 15 m object-based maps of land-cover change indicate 'Unchanged forest' as the land-cover class for portions of this clearing. Although less common than in the pixel-based classification maps, the presence of the 'Non-forest to forest' class in all five classifications is an error within the classifications of this particular area, as within the region shown, there were no areas identified as new forest growth within the 6 years between images. As one might expect, minor land-cover changes such as access roads to wells are better identified at finer resolutions between 1 and 5 m, although none of the maps fully and accurately identify the entire extent of these smaller changes to the forest, most likely due to the smoothing applied to the pixel-based classifications, and the aggregation inherent in GEOBIA classifications. Varying illumination and view angle effects in the aerial imagery may also have played a role in limiting the ability to identify small changes, as well as co-registration differences at the 1 m scale.

The most common classification errors for both methods came from similarities between DN values of forest pixels or objects and other vegetated pixels or objects. This led to the misclassification of some agricultural fields as forest, because brightly illuminated forest had similar reflectance to other vegetation. Classification error of this type explains some of the land-cover change classified as 'Non-forest to forest'.

5.2. Land-cover change map accuracy assessment comparison

The 1 m object-based classification was the most accurate of all the classification method/spatial resolution combinations. The most accurate pixel-based map of land-cover change produced (Table 1) was the 5 m map at 81.6%, although the 1 and 2 m maps had only

Table 1. Summary of overall accuracy, quantity disagreement, and allocation disagreement for pixel- and object-based maps of land-cover change as a function of pixel size.

Classification method	Pixel size (m)	Overall accuracy (%)	Quantity disagreement	Allocation disagreement
Pixel-based	1	81.3	0.11	0.07
	2	81.3	0.12	0.07
	5	81.6	0.12	0.06
	15	76.0	0.17	0.07
	30	75.6	0.12	0.12
Object-based	1	87.1	0.07	0.07
	2	80.1	0.14	0.06
	5	82.3	0.12	0.06
	15	74.7	0.21	0.06
	30	76.0	0.12	0.13

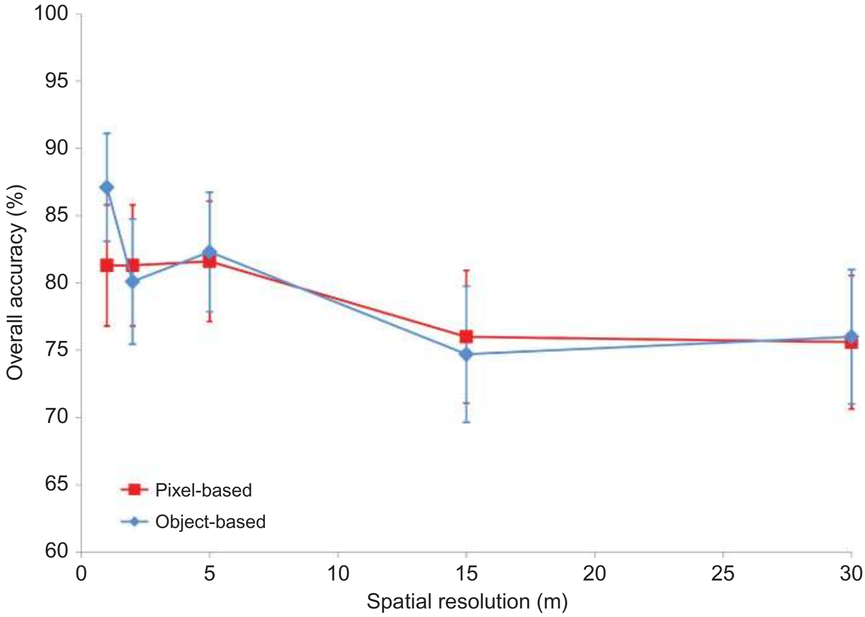

Figure 6. Comparison of overall accuracy of land-cover change maps for pixel-based and object-based classification methods of five spatial resolutions. Error bars indicate 95% confidence interval.

slightly lower accuracy. The 15 and 30 m resolution map accuracies were notably lower, at 76.0% and 75.6%, respectively. For the object-based series of maps, the most accurate classification was the 1 m map at 87.1%, and the 5 m map at 82.3% was the second most accurate classification. As with the pixel-based classification, the 15 and 30 m object-based change maps had notably lower accuracies than the finer resolution classifications.

Figure 6, showing the uncertainty associated with these accuracies, indicates that the 1 m object-based classification was statistically more accurate than the 15 and 30 m maps of both pixel- and object-based methods. This result suggests that fine spatial resolution does seem to favour GEOBIA. Despite this finding, the classifications at scales of 2–30 m were not statistically different, suggesting that if cost and availability limit access to the very finest scales, moderate resolution data, analysed using pixel-based classification methods, can suffice in place of 2–5 m data and the more complex, object-based classification. However, for any single spatial resolution, the accuracy of the object-based change map is not statistically different from that of the pixel-based change map at the same resolution. This general lack of statistical difference between object- and pixel-based methods applied at the same scale suggests that pixel-based classification combined with the post-classification filtering process, which eliminated some of the salt-and-pepper effect common to pixel-based classifications, may be as effective as GEOBIA change analysis, especially at scales coarser than 1 m.

The quantity disagreement values, which give information on the error in the relative proportion of the classes in the map, range from 0.07 to 0.21 for both pixel- and object-based classification methods (Table 1). The quantity disagreement values were more consistent across scales for the pixel-based classification than the object-based classification, which had both the lowest and the highest values observed. For both the pixel- and object-based classifications, the highest quantity disagreement values were found for maps produced with 15 m pixels. Allocation disagreement was very similar (0.06–0.07) for the object-based and pixel-based maps for pixels of 2–30 m, but was noticeably higher at the 30 m pixel scale (0.12–0.13). This suggests that at coarser spatial resolutions, well site spectral properties become less separable for pixel-based classifications. In combination, the two measures of accuracy imply that the proportion of pixels assigned to each class was a source of error more often than the spatial allocation of classes within the classifications.

Error matrices of the 1 and 30 m pixel- and object-based maps are shown in Table 2. These error matrices were chosen because they illustrate the range of spatial scales considered. Generally, the unchanged classes have relatively high producer's and user's accuracy, ranging between 61% and 100%. The changed classes have low user's accuracy (0–25%), especially the 'Non-forest to forest' class, which occurred only infrequently, and also generally have low producer's accuracy. The 'Forest to non-forest' class has notably high producer's accuracy for the pixel-based classifications (86% for both the 1 and 30 m classifications), although for the GEOBIA classification, the producer's accuracy for the 30 m data is only 29%.

5.3. *Assessment of land-cover change attributed to new gas well clearings*

The accuracy assessment of the estimates of proportion of land-cover change within the randomly selected 180 new gas well clearings as a function of scale (Figure 7) indicates that the GEOBIA classification was most accurate at 1 m resolution, with an overall trend of decreasing accuracy from 71% to 58% as pixel size coarsened from 1 to 30 m. The opposite is true of the pixel-based classifications – the accuracy generally increased from 59% at 1 m resolution to 80% at 30 m resolution, the highest value observed over all scales and both methods. For pixel-based methods, coarsening of the resolution reduces the within-class variability, and therefore will likely improve classification accuracy, as long as the classes are still spatially resolved. In addition, coarsening the spatial resolution, at least for the very finest scales, should reduce the effects of any co-registration errors. At even coarser spatial resolutions than the range studied here, the accuracies of both classifications would likely decrease, as the pixel size starts approaching the scale of the well clearings. Presumably, the high contrast between the cleared and undisturbed forest associated with well clearings is important in making this class distinguishable at a 30 m pixel size, since at this scale the average well clearing size of 0.9 ha would comprise approximately only 10 pixels, and the very smallest well clearing of 0.2 ha only 2 pixels.

In portions of the study area, clearing of forest for natural gas well development was clearly the largest driver of forest to non-forest land-cover change during the period studied (Figure 5). However, well site permits indicate spatial clustering of the land disturbance, particularly in the eastern third of the county (Figure 1). This raises the question of how the patterns of observed change vary with the spatial extent of the area studied. The study site was therefore divided on a 3 km $\times$ 3 km grid. From the resulting 168 grid cells, a random sample of 10 cells that also met a definition of high well activity (defined as 13 or more active gas well drilling operations per cell) was selected. Within these areas of intense gas well development, the Forest to non-forest change class made up between 2.7% and 16.9% of the land area. Part of this observed variability is due to the fact that not all well permits were sited in forest areas; many permits were located in cultivated fields and pasture. In comparison, the Forest to non-forest change class represented 9.3% of the county as a whole, indicating that gas well clearings merit further study as strong, albeit localized, drivers of land-cover change and forest fragmentation in this region.

Table 2. Error matrices for maps of land-cover change for (a) and (c) pixel-based and (b) and (d) GEOBIA classification methods at 1 and 30 m spatial scales.

(a) Accuracy measures for 1 m pixel-based map

	Reference					
Classified	1	2	3	4	Total	User's accuracy (%)
1	174	1	1	17	193	90
2	1	6	0	15	22	27
3	9	0	2	7	18	11
4	5	0	0	62	67	93
Total	189	7	3	101	300	
Producer's accuracy (%)	92	86	67	61		

Overall accuracy = 81.3%

(b) Accuracy measures for 1 m object-based map

	Reference					
Classified	1	2	3	4	Total	User's accuracy (%)
1	156	0	1	11	168	93
2	5	4	0	5	14	29
3	9	0	0	3	12	0
4	5	1	0	80	86	93
Total	175	5	1	99	280	
Producer's accuracy (%)	89	80	0	81		

*Overall accuracy = 87.1%

(c) Accuracy measures for 30 m pixel-based map

	Reference					
Classified	1	2	3	4	Total	User's accuracy (%)
1	144	0	1	10	155	93
2	14	6	0	9	29	21
3	11	0	1	6	18	6
4	20	1	1	76	98	78
Total	189	7	3	101	300	
Producer's accuracy (%)	76	86	33	75		

Overall accuracy = 75.6%

(d) Accuracy measures for 30 m object-based map

	Reference					
Classified	1	2	3	4	Total	User's accuracy (%)
1	142	17	18	7	184	77
2	9	7	0	9	25	28
3	0	0	4	12	16	25
4	0	0	0	68	68	100
Total	151	24	22	96	293	
Producer's accuracy (%)	94	29	18	71		

*Overall accuracy = 76.0%

Notes: *Object-based classifications have area-weighted overall accuracy but otherwise accuracies are reported on a per-object (pixel) basis.
Class 1 = 'Unchanged forest', Class 2 = 'Forest to non-forest', Class 3 = 'Non-forest to forest', and Class 4 = 'Unchanged non-forest'.
Because of the GEOBIA sampling procedure, the number of samples in each reference class, and overall, is not consistent between the different error matrices.

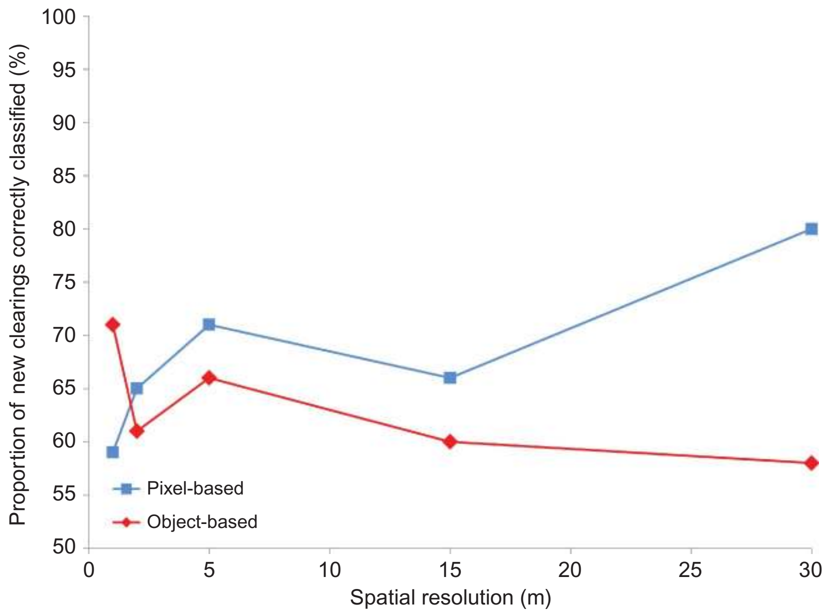

Figure 7. Accuracy comparison of the proportion of correctly identified land-cover change for 180 well clearings for pixel-based and object-based classification methods.

6. Conclusion

The primary focus of this research was to evaluate whether GEOBIA classification is more accurate when applied to fine spatial resolution data than to moderate resolution data, an assumption that seems to be implied by the common assertion that GEOBIA development was driven by the increased availability of high-resolution imagery (Blaschke et al. 2000; Hay and Castilla 2008). The study was carried out in the context of an evaluation of land-cover change associated with forest clearings for new gas well sites. The gas well sites varied in size from 0.2 to 9.2 ha, with an average size of 0.9 ha, and the pixel size of the imagery used varied from 1 to 30 m. The results of this study confirm that assumption: the 1 m GEOBIA classification was found to be significantly more accurate than GEOBIA classifications that used 15 and 30 m data (Figure 6). However, the 2 and 5 m GEOBIA classifications were not statistically more accurate than the GEOBIA classifications using coarser resolution data, suggesting that the benefits are only apparent at the very highest spatial resolutions, at least within the context of the particular application of this study, mapping forest clearings.

The second aspect of this research was to compare object-based and pixel-based classifications across multiple scales. The 1 m GEOBIA classification was found to be more accurate than the 15 and 30 m per-pixel classification, and more accurate than the GEOBIA classifications at those resolutions, as noted above. Thus, the combination of high spatial resolution data and GEOBIA is preferable to moderate resolution data, irrespective of the classification method. However, when the two methods are compared at any one spatial resolution, including the 1 m scale, the accuracies were not found to be significantly different (Figure 6). This finding calls into question the benefit of GEOBIA for forest clearings mapping, especially considering the time required to develop complex rulesets, the classification method chosen for this study. Traditional pixel-based classification modified using a simple post-classification smoothing technique appears to be a viable alternative to GEOBIA.

When the proportion of new well clearings correctly mapped was investigated (Figure 7), pixel-based classification generally increased in accuracy, and the GEOBIA classification accuracy declined, as the pixel size used changed from 1 to 30 m. Only at the 1 m scale was the GEOBIA classification more accurate than the pixel-based classification.

This research has implications for future studies focused on object-based and pixel-based classifications. Spatial resolution is only one of the characteristics of imagery that affect thematic map accuracy (Warner, Nellis, and Foody 2009b), and generalizing from these results will require consideration of the underlying mapping problem of interest. Object-based methods are potentially more effective than pixel-based methods if the classes have high internal variability, and the classes of interest cover large areas relative to the pixel size. Per-pixel methods are more likely to be successful where the classes of interest occur in patches that are at time relatively small.

One of the challenges of this work was to define a consistent and logical GEOBIA change detection accuracy evaluation procedure. The approach developed for this study served the needs of the project well, but further work in developing optimal accuracy evaluation methods should be a high priority.

Practical limitations would also be important if this procedure were to be conducted in an operational setting. The original 1 m imagery of the entire county required approximately 10 GB of disk space and took more than 4 h to segment and classify on a 3.2 GHz Quad Core i7 computer, with 24 GB of RAM. The large images also caused software crashes, and the large number of polygons generated in the GEOBIA analysis at 1 m appeared to exceed the file format limits. In practice, therefore, fine spatial resolution data may not be appropriate for large regional mapping applications. These problems reinforce the concern that high spatial resolution comes with trade-offs (Warner, Nellis, and Foody 2009b; Warner 2010).

The data used in this project consisted of US government NAIP imagery, which is increasingly used in research projects (e.g. Crimmins, Mynsberge, and Warner 2009) because of its minimal cost and relatively frequent repeat acquisition. However, the use of NAIP aerial imagery for evaluating land-cover change poses several distinctive challenges compared to other data sources. Mosaicking quarter quadrangle tiles collected over an entire growing season leads to differences in DN values across multiple image tiles as plant phenology, time of day, and illumination vary between image acquisition times. Histogram matching of overlap areas helped normalize some of these differences but some image tiles were still noticeably different. Also, although shadows tend to be consistent at least within individual quarter quadrangle tiles, they are challenging to classify correctly, especially within-forest shadows that may be misclassified as forest clearings.

The ideal for a project of the nature studied here would be to use satellite data that cover the entire study area in one image. This would reduce within-scene variations in phenology and illumination, at least for study areas of size similar to that in this study, and without notable climate gradients. However, scale does remain an important issue. Although 30 m imagery (such as Landsat) could potentially be used to monitor this type of land-cover change, it is unlikely that imagery coarser than 30 m spatial resolution would prove useful for observing this process, because the clearings average only 0.9 ha in size. The temporal resolution of the sensor also factors into the ability to accurately classify and assess land-cover change, because gas well clearings could potentially be cleared and re-vegetated with grass or shrubs in a relatively short period of time, making clearings more spectrally similar to the surrounding forest. Therefore, a satellite-borne data source with a spatial resolution finer than 30 m (such as the Advanced Spaceborne Thermal Emission and Reflectance Radiometer (ASTER)) and with the ability to acquire images at yearly intervals would be most effective for monitoring land-cover change associated with natural gas development.

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