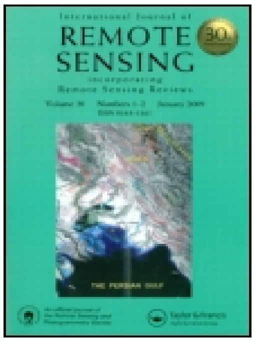

International Journal of Remote Sensing

ISSN: 0143-1161 (Print) 1366-5901 (Online) Journal homepage: http://www.tandfonline.com/loi/tres20

Mapping land cover and land use from object-based classification: an example from a complex agricultural landscape

Douglas G. Goodin, Kyle L. Anibas & Maksym Bezymennyi

International Journal of Remote Sensing, 2015
Vol. 36, No. 18, 4702–4723, http://dx.doi.org/10.1080/01431161.2015.1088674

Mapping land cover and land use from object-based classification: an example from a complex agricultural landscape

Douglas G. Goodin[a]*, Kyle L. Anibas[a], and Maksym Bezymennyi[b]

[a]*Department of Geography, 118 Seaton Hall, Kansas State University, Manhattan, KS 66506, USA;* [b]*Institute of Veterinary Medicine of NAAS, Kyiv, 03151, Ukraine*

(*Received 6 March 2015; accepted 20 August 2015*)

From its inception, land-use and land-cover mapping have been major themes in remote-sensing research and applications. Although frequently considered together, land use and land cover (LULC) are defined differently, with land use referring to the economic function of the Earth's surface and land cover to its natural or engineered biophysical cover. Land cover can be observed directly using remote sensing, but land use must be inferred from the cover type. In this study, we test whether object-based image analysis (OBIA) can improve the land-cover and land-use classification in a complex agricultural landscape located along the border between Poland and Ukraine. We quantitatively compared the results of OBIA-based *versus* per-pixel classifications for both land cover and land use, respectively. Our results show that land-cover classification was not significantly improved when OBIA-based methods were used. Although overall classification accuracy was modest, land-use classification was significantly improved when OBIA-based methods were applied using both spectral and spatial/geometric features of image objects, but not when spectral or spatial/geometric features were used independently. Our results suggest that in anthropogenically altered landscapes where the geometry and arrangement of surface spatial structure may convey land-use information, use of OBIA-based techniques may provide a powerful tool for improving classification.

1. Introduction

Land use and land cover (LULC) are related but distinct concepts, with differing definitions and relevance to different types of Earth's surface-cover analysis. In general, land cover refers to natural or human-engineered materials covering the Earth's surface, and is typically defined in biophysical terms (Comber, Fisher, and Wadsworth 2005). In contrast, land use refers to the function of the surface cover, which is usually expressed in economic terms (Dickinson and Shaw 1977). Land-cover materials can be observed directly using remote sensing, but land use must be inferred from land cover and additional data (Townshend et al. 1991). Although land use and land cover are distinct types of information, the methods used to extract them from imagery are similar, and despite the extensive remote-sensing literature in classification, optimal methods for determining land use *versus* land cover are not often considered (Franklin and Wulder 2002). The majority of classifications of LULC have been performed using statistical pattern or cluster finding methods applied in the spectral domain of the data, using individual pixels as the unit of analysis. More recently, machine learning and artificial intelligence methods such as artificial neural networks (ANNs), support vector machines

*Corresponding author. Email: dgoodin@ksu.edu

(SVMs), Kahunen (self-organizing) maps, and decision trees have been applied to classification problems (Hosokawa, Ito, and Hoshi 1999; Miller, Kaminsky, and Rana 1995; Mountrakis, Im, and Ogole 2011; Xu et al. 2005). These methods exploit the classification decision space in ways that parametric decision rules cannot, and thus can return more accurate results, especially when the distribution of the classification features deviates from the assumptions of parametric methods.

Although the extraction of thematic information using the spectral domain of the data remains a viable tool for image classification, exclusive use of the image's spectral domain sacrifices much of the information present in image data. Image data are inherently spatial, and exploitation of the spatial properties of the imagery can improve image classification (Li et al. 2014). The potential utility of spatial information for classification is particularly apparent upon the examination of imagery from agricultural landscapes, such as the one shown in Figure 1. The land cover present in these images is a mixture of herbaceous vegetation (mostly cultivated crops, but also some non-cultivated types), woody vegetation (trees), bare soil, artificial surfaces (concrete, asphalt, shingle, and other urban-associated cover), and small amounts of water. A variety of land uses are also apparent in the image. Clearly, more than one type of agricultural land use is represented here, and the visual cues that inform this observation are largely based on the sizes and shapes of the individual agricultural fields. Although such differences are readily discernible to the eye, a classification using the traditional means, utilizing spectral criteria, may not detect the differences between them. In other words, much of the relevant information for discriminating land use in these images is spatial, rather than spectral in nature. However, if these spatial properties are to be incorporated as usable dimensions in a classification feature space, a methodology for quantifying them is needed.

Use of remotely sensed information in the image spatial domain for LULC classification is not new. Some spatial methods make use of contextual information and image texture (Li et al. 2014; Warner 2011; Ryherd and Woodcock 1996; Swain, Vardeman, and Tilton 1981; Wang and He 1990; Wharton 1982). Textural transforms

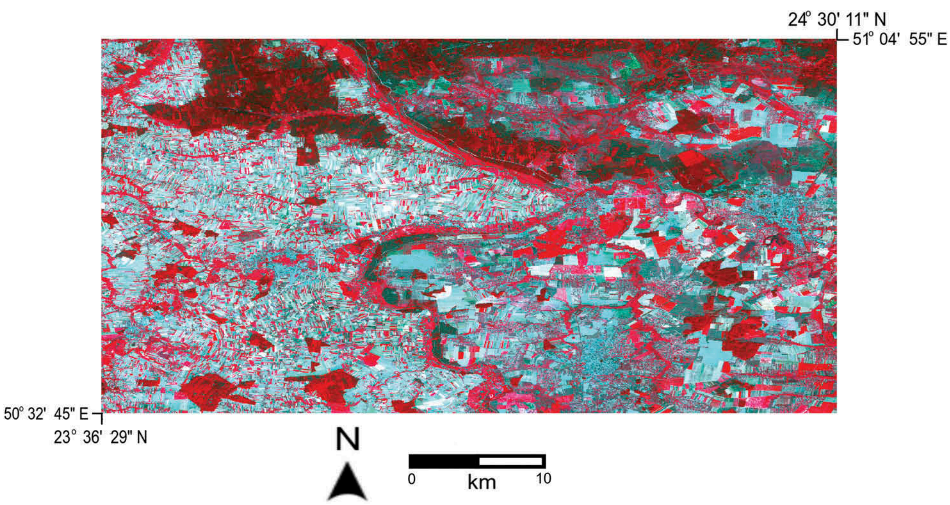

Figure 1. False colour composite composed of bands 5 (red), 4 (green), and 3 (blue) of the Landsat 8 OLI image used in this classification. Date of acquisition is 9 August 2013. Latitude and longitude coordinates for the lower left and upper right corners of the image are in degrees.

(e.g. Haralick) are used in image classification as extensions to the feature space, whereas in contextual classification, spatial proximity or the configuration of classified pixels is used as a 'second step' reclassifier (Townshend et al. 1991). In each case, the spatial unit of classification remains the individual pixel. However, as noted by Fisher (1997), pixels are not true spatial objects, and their ability to encode information from the spatial domain of an image is limited, at best. Object-based image analysis (OBIA, see Blaschke 2010) provides another suite of tools and methods for delimiting and quantifying spatial information in imagery, and use of OBIA-based methods for analysing remote-sensing data is increasing. Unlike textural transforms, which are generally calculated using moving window methods applied to uniformly shaped regions of pixels, objects are natural regions of relative homogeneity within the image. As such, objects may have varying sizes, shapes, and spectral properties, all of which may contain fundamental information about the object itself and about the underlying landscape depicted in an image scene. Image objects are therefore true spatial objects (Castilla and Hay 2008), and use of OBIA techniques offers a promising route by which spatial information can be used in classification problems (Aguirre-Gutiérrez, Seijmonsbergen, and Duivenvoorden 2012; Koch, Mohler, and Goodin 2007; Stefanski, Chaskovskyy, and Waske 2014). Object-based classification has been applied successfully in a number of agricultural LULC classifications (Duro, Franklin, and Dubé 2012; Ruiz et al. 2011; Peña-Barragán et al. 2011; Castillejo-González et al. 2009; Lucas et al. 2007).

The advantages (both realized and potential) of using object-based classification methods can be understood in terms of classification feature space (Richards and Jia 2006). In conventional per-pixel classification, each pixel is typically represented by spectral reflectance in a number of discrete spectral bands (determined by the imaging sensor from which the imagery was acquired); thus, the dimensionality of the feature space is determined by the number of these bands. On the other hand, image objects, such as those created by image segmentation, are characterized by their spatial and geometric properties as well as by their spectral ones (Navulur 2007). These object spatial/geometric properties can become part of the classification feature space, provided adequate methods are available to quantify them. When applied to the land-use/land-cover classification problem, these spatial/geometric features may yield classification features that are not apparent when only spectral features are used. For example, the spectral properties of land cover can change rapidly over time, in response to canopy phenology or management practices. Spatial properties, however, are liable to be more persistent and invariant over time, especially in agricultural areas where fields often retain the same boundaries (and therefore the same shape, size, etc.) even as their cover changes due to phenological development or management practices.

Given the success of object-based classification applied to remotely sensed imagery, and the apparent relationship between land use and agricultural field shape noted above, we set out to test whether the extended feature space associated with object-based classification methods might be useful for addressing the problems of discriminating LULC in a landscape where a variety of land uses, including several types of agriculture, are concentrated in a relatively small area and intermingled with each other. Our test is carried out in two parts. First, we will determine whether object-based methods can improve the classification of land cover. Since land cover is defined more in terms of its biophysical properties, we hypothesize that the results of these classifications will not be significantly different. We then test whether object-based methods improve the classification of land use. Our hypothesis in this instance is that classification will be significantly improved using object-based methods.

2. Study area

The study area for this analysis was an area along the Ukraine–Poland border, encompassing parts of Volyn oblast (on the Ukrainian side) and Lubelski volveldeship on the Polish side (see Figure 2). We chose this area primarily because it is heavily agricultural, and because it encompasses a variety of agricultural practices that result in fields with contrasting sizes and shapes. It therefore provides a challenging landscape on which to test whether object-based methods can improve land-cover or land-use classification.

The contrast in land-use pattern across the study area is largely due to the economic forces that have shaped, and continue to shape, agricultural practices in the area. Although both countries featured socialist economies during much of the twentieth century, Ukraine was a part of the Soviet Union and subject to centralized Soviet agricultural planning, characterized by collectivized and heavily mechanized production. Poland also had collectivized agricultural planning, but without the same levels of mechanization practiced in Ukraine (Kuemmerle et al. 2006). Although more than two decades have passed since the end of collectivized agriculture, the visual contrast between these two systems is still apparent in Landsat images of the study area (see Figure 1). Agricultural fields on the Polish side of the border tend to be smaller, more elongated, and arranged in a more irregular pattern. Fields on the Ukrainian side are generally larger and more regularly shaped, indicative of the widespread use of machinery (but note that many of the formally extensive fields on the Ukrainian side are now being subdivided, making them more similar to fields on the Polish side). Although field size and shape are different across the border, similar crop rotation practices continue to be used on both sides of the border, and the crops produced are also similar. Both types of fields were used for commercial production. Although not as initially apparent as the previous two patterns, a third, non-commercial agricultural pattern is also present on both sides of the border. This pattern consists of very small plots (typically <25 ha) belonging to individuals or single families and used mainly for household production (Heymann et al. 1994). These small plots were (and are) typically maintained by hand and not subject to crop rotation as in the other fields.

Although the contrasting cross-border agricultural patterns in our study area are noteworthy, our primary interest in this analysis is not in these differences *per se*, nor is

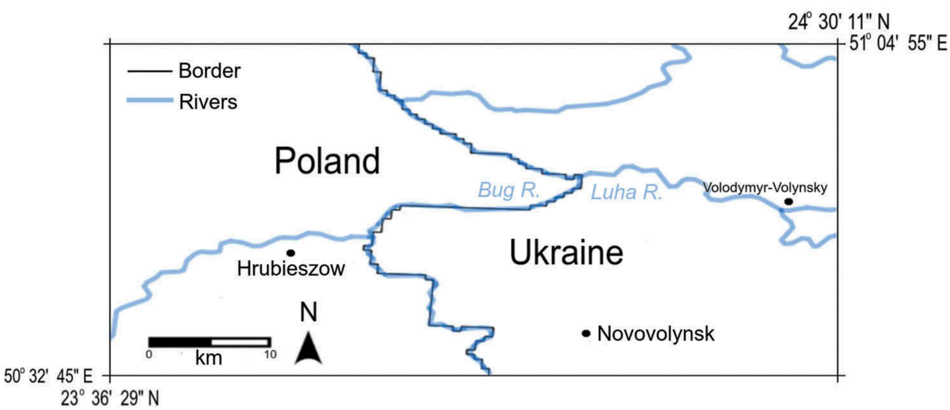

Figure 2. Map of the study area. Latitude and longitude coordinates for the lower left and upper right are in degrees.

it to analyse the history of agricultural practices and patterns in the transborder area. We chose this study area because it provides a clear example of a region where several contrasting land covers and agricultural land uses occur in close proximity to one another, and where cues to LULC class might be contained in the shapes and sizes of individual parcels, as well as in their spectral properties. It therefore provides a challenging landscape on which to test whether object properties can improve LULC classification.

3. Methodology

To determine whether the use of an object-based approach can improve classification, we compared object-based and per-pixel classifications. Because we had first-hand knowledge of the study site, and in order to keep the comparisons between the two types of classifications manageable, we compared only supervised classifications. Within the constraints imposed by the two contrasting methods, we tried to make our object-based and per-pixel classification procedures as parallel as possible; thus, we used the same single Landsat Operational Land Imager (OLI) image for both classifications, as well as similar training techniques and decision rules. We also used similar accuracy assessment methodologies for both classification types, although some changes had to be made to accommodate the object-based assessment.

3.1. Imagery

The image chosen for this analysis is a Landsat 8 OLI image acquired on 9 August 2013 (Figure 1). Bands 2–7 were used in this analysis. Although the full frame of this image had some cloud cover, our chosen area was clear of any visible clouds. The acquisition time of the image (late summer, post-harvest) is not optimal for classification of agricultural land from a single image, since many of the fields were bare or fallow. At the time of analysis, this was the only recent Landsat 8 image cloud-free enough to use. Examination of the image shows that the contrasting land patterns described in Section 2 are apparent. To improve the capability for segmenting small parcels, we pan-sharpened the multispectral OLI image using the Bayesian data fusion algorithm (Fasbender, Radoux, and Bogaert 2008), with the λ parameter set to the default value of 0.9999, as implemented in the European Space Agency's Optical Radar Federated Earth Observation (ORFEO) toolbox (Inglada and Christophe 2009).

3.2. Classification schemes

Although our focus in this analysis was mainly on agricultural land use, it is apparent that several other types of land uses or land covers (e.g. forest, urban, water) are present in the study area. Our classification schemes therefore needed to be comprehensive enough to accommodate a number of types of agricultural land use and cover, as well as including some non-agricultural uses. For land cover, we chose a subset of classes based on the International Geosphere–Biosphere Programme (IGBP) classification scheme (Townshend 1992, see Table 1). The IGBP scheme places all cropland into a single category, but separates woodlands into several types. We aggregated the woodland classes, since many of the forested areas in the study site were artificially cultivated.

For the land use, we needed a scheme that differentiated between the commercial agricultural patterns found mainly on the Ukrainian side of the border (i.e. larger,

Table 1. Land-cover classification scheme.

Class number	Class name	Description
1	Artificial/urban	Includes all urban surfaces, built areas, industrial areas, and roads.
2	Bare	Mostly consisted of post-harvest or fallow agricultural fields.
3	Grassland or Herbaceous cover	Cover composed of herbaceous or graminoid species. Included crops, managed areas (e.g. pastures), and naturally occurring grassland cover.
4	Woodland	Includes areas of woody vegetation. This category includes both coniferous and mixed parcels and may include some areas of shrubland or woody regrowth.
5	Wetland	Consists of areas with permanently or seasonally flooded or waterlogged soils, with vegetation cover composed or reeds, rushes, and sedges.
6	Water	Includes natural and artificial lakes, ponds, and streams.

Note: Categories are derived from the IGBP land-cover scheme.

square-shaped fields) *versus* those on the Polish side (smaller, more elongated fields). We therefore used a modified form of the Coordination of Information on the Environment (CORINE) land-use/land-cover scheme developed by the European Environment Agency (Heymann et al. 1994, see Table 2). Although not exclusively a land-use classification scheme (some of its classes are land cover, see Tomaselli et al. 2013), we chose CORINE as a basis for our cover classification because it was specifically designed to accommodate the type of land use found throughout Europe. We modified the CORINE scheme by subdividing type 2.1.1, non-irrigated arable land, into two new classes, one consisting of larger, regular fields and the other of smaller ones. We recognize that this division is somewhat subjective, but we nevertheless assert that the differences in agriculture practices, combined with the morphological difference, are enough to warrant dividing them. Note that whereas the arable type 1 class is defined based on land use from the Polish side, it can also occur on the Ukrainian side of the border. We also altered the definitions of some of the pasture and wetland classes, to more accurately match practices we observed during visits to the study area.

3.3. Classification

All classifications were performed using the Landsat 8 OLI image acquired in August 2013 (Figure 1). Although it is well known that classification accuracies improve when multi-date imagery is used (Esch et al. 2014; Prishchepov et al. 2012), we used a single date for this exercise. We did this because no other suitable OLI images were available at the time of the analysis and because our objective was direct comparison of the object-based and per-pixel methods. Similar methods were used for the LULC classifications.

3.3.1. Object-based classifications

Unlike per-pixel classifications, object-based methods involve two distinct steps: (1) segmentation (including object parameter calculation); and (2) classification. In object-based analysis, segmentation is a key step. Methods for selecting and

Table 2. Land-use classification scheme.

Class number	Class name	Description
1	Artificial/urban	Amalgamation of CORINE Class 1. Includes all urban surfaces, built areas, industrial areas, and roads.
2	Arable land, Type 1	Based on CORINE Class 2.1.1. Consists of arable land in rotation, produced for commercial uses. Generally, characterized by smaller, elongated fields in close proximity and often laid out in contrasting directions; can be bare or actively growing.
3	Arable land, Type 2	Based on CORINE Class 2.1.1. Consists of arable land in rotation, produced for commercial uses. Characterized by larger fields with regular, generally squarer shapes; can be bare or actively growing.
4	Pasture/abandoned	An amalgamation of CORINE Classes 2.4.3 and 2.3.1, consisting of former agricultural land but without a cropping for at least 5 years and often used for grazing.
5	Heterogeneous agriculture	Same as CORINE Class 2.4.2. Consists of juxtaposition of very small fields, with individual field sizes often less than 25 ha, frequently interspersed with houses. Used for permanent crops (i.e. not in rotation), mostly for household consumption, although some may be sold or traded.
6	Forest – mixed	Same as CORINE Class 3.1.3. Consists of mixed broad-leaf and coniferous species, frequently planted, rather than natural.
7	Forest – coniferous	Same as CORINE Class 3.1.1. Forest dominated by coniferous species. Usually planted, rather than natural.
8	Wetland/pasture	Areas that meet the definition for CORINE Class 4.1.1 (inland marsh), but that are used at least seasonally as pasture. Often found along riparian areas.
9	Water	A combination of CORINE Classes 5.1.1 and 5.1.2. Includes both waterbodies and flowing water courses

Note: Categories are modified from the CORINE classification scheme.

evaluating segmentation quality (e.g. Möller, Lymburner, and Volk 2007; Unnikrishnan, Pantofaru, and Hebert 2007) have generally suggested that optimal segmentations should minimize internal heterogeneity and maximize the contrast between a segment and its neighbours. Because of the nature of the application used here, where the sizes and shapes of objects are hypothesized to be important LULC discriminators, an effective segmentation must define objects with a range of sizes and shapes. Thus, we chose the edge-detection segmenter implemented in the ENVI Zoom module, v4.6 (Excelis Visual Information Solutions 2008). Unlike other methods we tried (e.g. region-joining methods), this method allowed for a range of segment sizes, while at the same time minimizing bias towards any particular object shape.

Since any segmentation algorithm is dependent on the parameters under which it was run, we experimented with a number of parameter settings. Determination and evaluation of these parameters are less analytically straightforward compared with the object heterogeneity metrics, although some methods have been suggested (e.g. Clinton et al. 2010). We used subjective methods based on visual comparison of the segmentation superimposed onto the original image. Based on these evaluations, we selected a segmentation parameter (scale level) of 80, with a merging threshold of 40.

Following segmentation, attributes were calculated for each image object. ENVI Zoom calculates a number of object attributes, some of which yield similar information. We divided these attributes into two types, spectral and spatial. The spectral attributes were those that were related to the reflectance properties of the objects and their component pixels. The spatial attributes included those derived from object geometry and object texture. We chose to group the textural metrics along with the geometric ones into the spatial category, because their calculation required information from neighbourhoods of pixels, and therefore represented spatial information in ways that object-based reflectance values did not. These features form the inputs to the classification algorithm, similar to how spectral reflectance features are for per-pixel methods.

For classification, we used an SVM. SVMs are a class of kernel-based machine learning algorithms, which have been shown to be effective for classifying a wide variety of data types (Cristianini and Shawe-Taylor 2000), including remote-sensing data (Mountrakis, Im, and Ogole 2011; Richards and Kingsbury 2014). We implemented SVM classification following the procedure suggested by Hsu, Chang, and Lin (2010). Using this approach, OLI reflectance data (for the per-pixel classification) and metrics created from segmentation (for the per-pixel classification) were first linearly rescaled to the range −1.0 to 1.0. Rescaling in this way circumvents problems created by differences in the numeric range between attributes (Hsu, Chang, and Lin 2010). For the kernel model, we selected the radial basis function (RBF), which is capable of both non-linear and linear mapping of input values into higher-dimensional classification space (Keerthi and Lin 2003). Optimal values of the penalty (C) and kernel (γ) parameters for the RBF model were selected using a grid-search method, as suggested by Hsu, Chang, and Lin (2010). Once optimal parameter values were determined, the SVM model was applied to all objects in the image using the TrainImagesClassifier tool from the ORFEO toolbox (Inglada and Christophe 2009), yielding a classified product. All SVM calculations were performed using the LIBSVM v.3.2 library (Chang and Lin 2011). The objects used to train the SVM were selected interactively from the image, guided by field notes and photographs from an *in situ* survey of the Ukrainian part of the study area (see Section 3.4), supplemented by visual interpretation of high-resolution GoogleEarth imagery, for both of the Ukrainian and Polish sites. The training objects for each class were selected from multiple locations throughout the image, in order to obtain a representative sample.

3.3.2. Per-pixel classification

To maintain parallel methods, the per-pixel classifications were also carried out using a supervised SVM model. Training samples were taken from the image from the same areas where the training objects were selected for the object-based analysis. These training samples were used to develop an SVM model using the LIBSVM tools similar to that in the object-based analysis. The model was applied to the image using the ORFEO toolbox TrainImagesClassifier tool (Inglada and Christophe 2009).

3.4. Accuracy assessment

Accuracy was assessed based on the two surveys conducted on the Ukrainian side of the study area (June 2012 and September 2013), supplemented by visual interpretation of high-resolution imagery from GoogleEarth. As in all other phases of this analysis, we strove to use comparable methods for both per-pixel and object-based classifications. However, the nature of the segmented *versus* non-segmented images necessitated some slight difference in the evaluation of the accuracy of the classifications (Gao and Mas 2008; Dingle Robertson and King 2011). In both cases, we used a suite of well-understood metrics, including overall accuracy, categorical accuracy, producer's accuracy, and user's accuracy (PA and UA, respectively), and the kappa statistic for evaluating the relative strength of the results. Extraction of an evaluation sample differed somewhat, however. For the per-pixel sample, we selected point samples from 271 reference sites. Some of these were selected *in situ* during the field survey, whereas others were randomly selected from the fine-resolution GoogleEarth imagery. Each of these sites was assigned to its proper class, forming the reference data set. These sites were then compared to the same points on the per-pixel classified images, using the aforementioned techniques.

For the object-based classifications, accuracy evaluation was complicated by the spatial nature of the segmented imagery. The spatial unit of the reference data was points, but the spatial unit of the object-based classifications was image segments, which, unlike points, have spatial area as an inherent property. To circumvent this problem while still using the existing ground-truth data, we superimposed the point sample over the object-based classification map, and then used each object in which a point sample occurred as the accuracy assessment sample. Land use in these objects was then evaluated using field notes and photographs to determine whether it matched its predicted category. If we determined that the majority of the objects matched their predicted class, it was considered to be accurately classified. In cases where more than one point from the original accuracy sample fell into the same segment, that segment was only counted once, and another segment from the same predicted class was randomly selected for evaluation. This ensured that each accuracy assessment was based on an equal number of samples.

4. Results and analysis

4.1. Land-cover classification results

Results for the land-cover classification show that object-based classification resulted in a more accurate map compared to per-pixel classification (Table 3); however, pairwise comparison of the kappa values showed no significant difference (Z = 0.33, p = 0.63). There were some minor differences in the individual categorical accuracies between the two classifications. For example, UA for the grassland category was somewhat lower for both per-pixel and object-based classifications, compared to the corresponding PA. In general, though, the overall accuracy and error metrics for both classifications were quite similar. This result was in general agreement with that of Duro, Franklin, and Dubé (2012), who also found no improvement in agricultural land-cover classification accuracy when using object-based classification.

4.2. Land-use classification results

Since land use seemed to be much more closely tied to object shape, we conducted three separate object-based classifications to test this hypothesis more in-depth. These three classifications were: (1) using both spectral and spatial/geometric object features (henceforth referred to as OBIA-combined); (2) using only object spectral features (OBIA-spectral); and (3) using only spatial and geometric object properties

Table 3. Error matrices and classification accuracy results for the per-pixel and object-based land-cover classifications.

	Reference						
Classification	Artificial	Bare Soil	Grassland/ Herbaceous	Woody	Wetland	Water	UA
Per-pixel classification							
Artificial	12	1	0	0	0	1	0.86
Bare soil	1	120	1	3	2	0	0.94
Grassland/herbaceous	1	4	11	3	2	0	0.53
Woody	2	2	1	37	0	1	0.86
Wetland	0	0	1	2	26	0	0.90
Water	0	0	0	0	1	9	0.90
PA	0.80	0.95	0.79	0.82	0.84	0.82	
Accuracy = 0.88							
Kappa coefficient = 0.835, kappa coefficient variance = 0.0311							
Object-based classification							
Artificial	13	1	0	0	0	2	0.81
Bare soil	3	123	0	0	8	0	0.92
Grassland/herbaceous	0	2	12	4	0	0	0.67
Woody	0	1	1	39	1	0	0.93
Wetland	0	0	1	2	21	0	0.88
Water	0	0	0	0	1	9	0.90
PA	0.81	0.97	0.86	0.87	0.68	0.82	
Accuracy = 0.89							
Kappa coefficient = 0.832, kappa coefficient variance = 0.0883							

Note: UA and PA indicate user's accuracy and producer's accuracy, respectively.

(OBIA-spatial). Each of these was compared to a classification carried out using a supervised per-pixel technique.

The results of the object-based classifications are mixed (Tables 4–7). Accuracy metrics for the four classifications show that the OBIA-combined approach yielded the highest overall classification accuracy compared to any of the other approaches. Overall accuracy for this classification was 0.75, a modest level of accuracy, at best and below suggested standards for remote-sensing classifications (Thomlinson, Bolstad, and Cohen 1999). However, because the classification was carried out under demanding data conditions (a single image date acquired at a non-optimal time) and featured a classification scheme with a number of difficult-to-discriminate classes, we consider it a viable result. The OBIA-spatial and per-pixel classifications both had essentially overall accuracies. The OBIA-spectral classification outperformed the per-pixel and OBIA-spatial classifications, but was less accurate than OBIA-combined. Pairwise comparisons of the overall kappa values for each of the four classifications show that the improvements in accuracy gained from using both spectral and spatial/geometric object properties as classification features were highly significant ($p < 0.01$) when compared to per-pixel classification and object-based classification using only spatial object properties. The OBIA-combined classification also outperformed the OBIA-spectral classification, although not as significantly as for the other methods (see Table 8). Pairwise kappa comparison for all other

Table 4. Error matrix and accuracy assessment for per-pixel land-use classification.

	Reference									
Classification	Artificial/ urban	Arable 1	Arable 2	Pasture/ abandoned	Heterogeneous agriculture	Forest – mixed	Forest – coniferous	Wetland/ pasture	Water	UA
Artificial/urban	12	0	0	3	0	0	0	0	1	0.75
Arable 1	5	50	14	3	26	1	0	2	0	0.5
Arable 2	0	10	14	1	4	0	0	0	0	0.48
Pasture/abandoned	1	0	2	12	6	1	0	3	3	0.56
Heterogeneous agriculture	2	1	1	7	14	0	0	0	0	0.56
Forest – mixed	1	1	1	2	0	17	3	0	1	0.65
Forest – coniferous	0	0	0	0	0	5	9	0	1	0.6
Wetland/pasture	1	1	3	7	2	2	0	8	0	0.33
Water	0	0	0	1	0	0	0	0	9	0.9
PA	0.55	0.79	0.4	0.33	0.27	0.65	0.75	0.62	0.75	
Accuracy = 0.61										
Kappa coefficient = 0.52, kappa coefficient variance = 0.0011										

Note: See Table 2 for a complete definition of each land-use class.

Table 5. Error matrix and accuracy estimates for the object-based supervised classification that uses spectral features only.

	Reference									
Classification	Artificial/ urban	Arable 1	Arable 2	Pasture/ abandoned	Heterogeneous agriculture	Forest – mixed	Forest – coniferous	Wetland/ pasture	Water	UA
Artificial/urban	11	1	1	1	1	0	0	0	0	0.73
Arable 1	1	73	8	3	10	1	0	0	0	0.76
Arable 2	0	14	17	2	5	0	0	3	1	0.40
Pasture/abandoned	0	0	5	13	0	1	0	1	0	0.65
Heterogeneous agriculture	2	1	4	1	9	1	0	1	0	0.47
Forest – mixed	0	0	1	2	0	23	1	1	1	0.79
Forest – coniferous	0	0	0	0	0	5	10	0	0	0.67
Wetland/pasture	0	0	3	0	1	1	1	19	0	0.76
Water	0	0	0	0	0	0	0	0	10	1.00
PA	0.79	0.82	0.44	0.59	0.35	0.72	0.83	0.76	0.83	
Accuracy = 0.68										
Kappa coefficient = 0.61, kappa coefficient variance = 0.0012										

Note: See Table 2 for a complete definition of each land-use class.

Table 6. Error matrix and accuracy estimates for the object-based supervised classification that uses spatial features only.

	Reference									
Classification	Artificial/ urban	Arable 1	Arable 2	Pasture/ abandoned	Heterogeneous agriculture	Forest – mixed	Forest – coniferous	Wetland/ pasture	Water	UA
Artificial/urban	6	1	0	0	0	0	0	6	2	0.40
Arable 1	2	76	1	0	3	0	1	12	1	0.79
Arable 2	3	11	14	0	6	0	0	6	2	0.33
Pasture/abandoned	3	0	2	10	0	0	0	4	1	0.50
Heterogeneous agriculture	2	3	1	2	5	0	0	5	1	0.26
Forest – mixed	3	0	0	2	0	18	2	0	4	0.62
Forest – coniferous	0	0	0	0	0	3	12	0	0	0.80
Wetland/pasture	2	4	0	0	3	0	1	13	2	0.52
Water	0	0	0	0	0	0	0	0	10	1.0
PA	0.29	0.80	0.78	0.71	0.29	0.86	0.75	0.28	0.43	

Accuracy = 0.61
Kappa coefficient = 0.52, kappa coefficient variance = 0.0018

Note: See Table 2 for a complete definition of each land-use class.

Table 7. Error matrix and accuracy estimates for the object-based supervised classification that combines spatial and spectral features.

	Reference									
Classification	Artificial/ urban	Arable 1	Arable 2	Pasture/ abandoned	Heterogeneous agriculture	Forest – mixed	Forest – coniferous	Wetland/ pasture	Water	UA
Artificial/urban	12	1	0	0	1	0	0	0	1	0.80
Arable 1	1	85	3	0	5	1	0	0	1	0.89
Arable 2	0	9	21	2	5	0	0	4	1	0.50
Pasture/abandoned	0	0	2	12	2	1	1	2	0	0.60
Heterogeneous agriculture	1	3	1	1	12	0	1	1	0	0.63
Forest – mixed	0	0	2	2	0	21	4	1	1	0.72
Forest – coniferous	0	0	0	0	0	2	13	0	0	0.87
Wetland/pasture	0	1	0	0	2	1	1	17	1	0.68
Water	0	0	0	0	0	0	0	0	10	1.00
PA	0.86	0.86	0.75	0.71	0.44	0.81	0.65	0.68	0.67	
Accuracy = 0.75										
Kappa coefficient = 0.71, kappa coefficient variance = 0.0007										

Note: See Table 2 for a complete definition of each land-use class.

Table 8. Kappa values and *Z*-scores from pairwise comparison of kappa values for the four classifications.

			Z-scores			
Classification type	Kappa coefficient	Kappa coefficient variance	OBIA – spatial	OBIA – spectral	OBIA – combined	Per-pixel
OBIA – spatial	0.52	0.0018	–			
OBIA – spectral	0.61	0.0012	1.64			
OBIA – combined	0.70	0.0007	3.34*	2.1**		
Per-pixel	0.52	0.0011	0.00	1.88	4.52*	–

Note: In each pairwise comparison, the lower kappa value was subtracted from the higher one, yielding only positive *Z*-values.
* Indicates significance at $p < 0.01$.
** Indicates significance at $p < 0.05$.

classification methods (OBIA-spatial, OBIA-spectral, and per-pixel) did not result in any statistically significant differences.

5. Discussion

Results of the land-cover classification supported our initial hypothesis that use of spatial or geometric information would not improve the overall classification accuracy. Although the object-based method did produce higher overall accuracy, there was no significant difference between the kappa values for either classification. This result can be best understood by considering that land cover is defined primarily by its biophysical properties, which evidently are more closely tied to spectral reflectance than they are to the spatial properties of image objects. This shows, at least in this case, that not only does object shape not convey land-cover information (at least not to the same degree as spectral reflectance), but also the additional spectral information gained by grouping pixels into objects (i.e. the addition of object variance and spectral range) was not very useful in discriminating land cover. Our study also agrees with previous findings showing that the reduction of spectral noise that occurs when pixels are aggregated into objects does not necessarily improve land-cover classification results (Fung et al. 2008; Petropoulos, Kalaitzidis, and Vadrevu 2012).

Although the land-use classification results were more mixed than those for the land-cover classification, at least one of the results supports our hypothesis that object-based methods can improve the accuracy of land-use classifications. Use of purely spectral information, whether on a per-pixel or a per-object basis, produced statistically inseparable classification accuracy results, with neither approach much exceeding 60–70% accuracy and both approaches yielding results only about 50–60% better than random, as indicated by their kappa values (see Tables 4 and 5). Again, this suggests that reduction in spectral heterogeneity by image segmentation does not in itself significantly improve classification when applied to moderate-resolution data. Use of object shape-based features alone also yielded mediocre results, which were not significantly different from the per-pixel or OBIA-spatial classifications. This is perhaps not surprising, since classification using only spatial features is founded on the assumption that any single category of land use must be characterized only by a distinctive geometric form or textural composition, with little variation between objects. Even in an agricultural landscape, where object shape is dictated by land-use practice (and perhaps by terrain morphology), this is an unrealistic assumption. However, the fact that a geometry-only approach did manage to accurately classify over 60% of the reference sample, with significant improvement compared to random chance (as indicated by the kappa statistic, see Table 6), does support the contention that object geometry can provide useful information for classification. This contention is further supported by the much stronger results from the OBIA-combined classification (Table 7), which yielded significant improvement over all other methods. In this example, use of object spatial properties clearly helped reduce the interclass confusion resulting from spectral reflectance.

Visual comparison of the results of the OBIA-combined and per-pixel classifications (Figure 3) shows that per-pixel classification has much more fine-scale variability or heterogeneity, compared with object-based classification. This is not surprising, since the grain of this classification is much finer than for the object-based method, and the decrease in fine-scale heterogeneity is a previously observed effect of image segmentation (Blaschke et al. 2000). In OBIA-based classification, the unit of analysis (the object) is typically much more spatially extensive than an individual pixel, and since the entire object is assigned to a particular class, the resulting classification must appear smoother (i.e. more spatially homogeneous) compared with the per-pixel map.

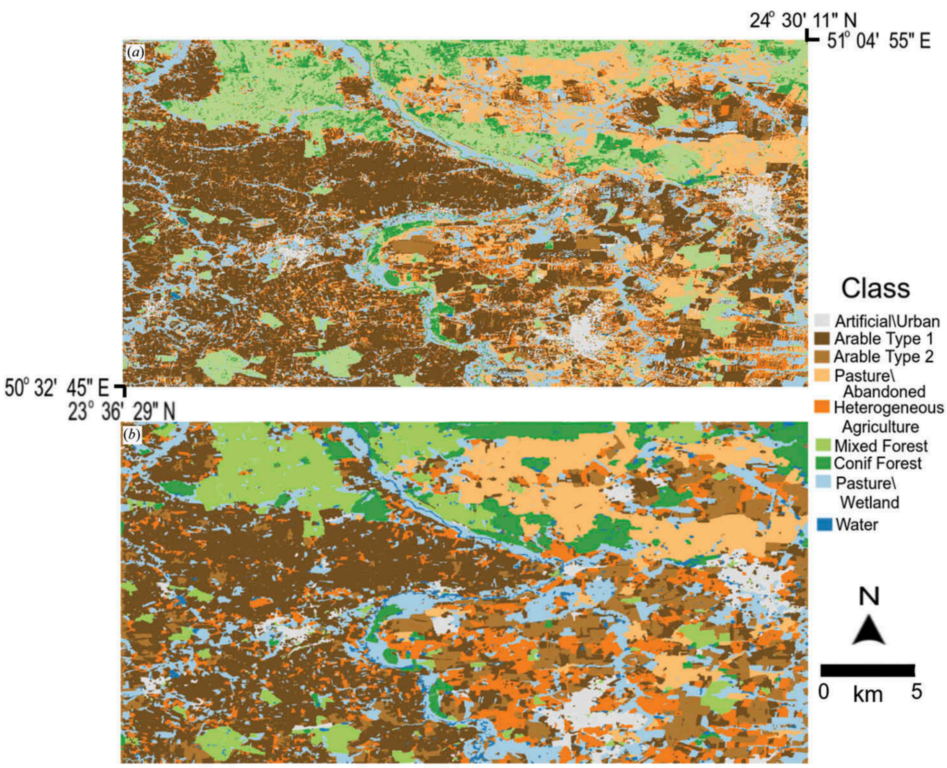

Figure 3. Results from the per-pixel (*a*) and OBIA-combined (*b*) classifications.

Although it is clear that the use of object properties improved the overall land-use classification, a main purpose of our analysis was to determine the extent to which it could be used to classify and discriminate between different agricultural land uses. Comparisons of accuracies for the classifications that used only spectral information showed mixed but mostly poor performance across all agricultural classes (see Tables 4 and 5). For the per-pixel spectral classification (Table 4), certain classes were classified reasonably well on some error metrics. For example, PA values for Arable Type 1 and Coniferous Forest both exceeded 70%, and UA for Artificial/Urban was 75%. Water classification performed comparably well in both UA and PA. However, none of the rest of the classes had high individual error metrics.

Use of only object spectral or spatial properties separately did not increase the classification accuracy in the agricultural categories. However, the combination of the two did improve the classification accuracy for all of the agriculture classes (Table 7). UAs and PAs for both of the Arable classes improved substantially, approaching 90% for Arable 1. The biggest improvement was in the Pasture/Abandoned class, which showed improvement compared with the other methods, although gains in accuracy were less pronounced relative to OBIA-spectral than they were for OBIA-spatial or the per-pixel classification. One class that did not show much improvement was the Heterogeneous Agriculture class, whose UA and PA were similarly low for all methods. Recall that this class was composed of very small fields, often of a grain size very similar to the resolution limit of the pan-sharpened imagery. This result shows some of the limitations of segmentation and object-based analysis. One notable exception to the general superiority of the OBIA-combined classification was the Wetland/Pasture class. This class tended to follow water courses and canals, and was most accurately classified by the OBIA-spectral method. Object spatial features were especially ineffective for discriminating this class, and it seems that the addition of spatial features actually reduced the accuracy of the OBIA-combined method for this class.

The classification results for the two forest categories were actually fairly similar for all of the four methods. This is likely due to the nature of these two classes. As noted earlier, the forested classes have a substantial history of manipulation, to the extent that many of the tree stands are artificially cultivated (Kuemmerle et al. 2011). This human manipulation perhaps has generated the spectral reflectance, structure, and texture patterns within the forested classes that apparently can be discriminated by all of the classification methods.

6. Conclusions

This analysis considered two questions about the use of object-based classification in an agricultural landscape: (1) can the use of object-based classification improve land-cover classification; and (2) can it improve land-use classification? The answers, in this example, were no and yes. For the land-cover classification, addition of spatial information resulted in no significant improvement to the classification accuracy. This result confirmed our initial hypothesis, which was based on the fact that land cover, defined in biophysical terms, would not necessarily have a geometric component. For land use, significant improvement was seen in the classification accuracy, but only when spectral and spatial/geometric features were used together. Since our chosen study site was a rather complex agricultural landscape, we also questioned whether OBIA methods improved the classification of agricultural land cover. Based on the results presented here, it did, but not as much as we anticipated that it might. Generally speaking, agricultural User and Producer class accuracies were improved, but not for every class.

Synergistic use of spectral and spatial information significantly improved the classification, at least in this example. There are several conclusions that can be drawn from this analysis, concerning the use of object-based techniques in classification. The landscape in this analysis is clearly one where land-use information is conveyed by the shapes, sizes, and textures of the objects, as well as by their spectral reflectance pattern. This is readily evident by inspecting the imagery used in the analysis (see Figure 1). Given the evident importance of geometry in this landscape, it is hardly surprising that the object-based technique outperformed the conventional per-pixel approach. What is noteworthy is the apparent importance of using the spectral and spatial information together, in order to achieve significantly improved classification results. Although the results presented here only hold for this particular example, they do suggest that an object-based classification approach using both spectral and spatial object features may improve land-use classification accuracy in landscapes where anthropogenic action has altered the landscape to yield a characteristic spatial pattern or geometry.

Whereas numerical evaluation of our results supports the use of object-based methods for land-use mapping, visual examination of the results suggests that the object-based method should not necessarily be uncritically accepted. Comparison of the two maps in Figure 3 shows that the OBIA results are much more spatially homogeneous than those from the per-pixel approach; however, this homogeneity does not in itself explain the difference in accuracy between the two classifications. It can be argued that while reference points used in the numerical accuracy assessment were significantly more likely to be correctly classified using the OBIA-based method, some of the spatial details of the scene may be lost or homogenized by the segmentation process and the subsequent assignment of all of an object to a particular class. This can be seen by comparing the classified maps (Figure 3) to the original image (Figure 1). The image shows finer-scale variability in land use that is not apparent in the OBIA-based maps, but can be seen in the per-pixel classification. This is particularly apparent in the forested and agriculture areas. While the per-pixel classification retains the spatial detail, this detail is apparently more likely to be incorrectly classified. Whether this homogenization of the final product is a problem depends on the goals of the classification and the desired minimum mapping unit of the final product.

Despite the success in increasing the land-use classification accuracy, there are some limitations in our analysis that subsequent applications of object-based methods might further explore. As noted in the Methods section, we used only a single image for our analysis, which was acquired late in the growing season when many of the crops had already been harvested. Although we chose this image because at the time of our analysis it was the only suitable one available, use of it added to the difficulty of the classification. Clearly, none of the methods used performed especially well in classifying the image. However, our objective in this analysis was to compare the relative accuracies of the methods, and our results support the use of OBIA-based classification for problems of this type. Improvements in classification accuracy could likely be achieved using multi-date classification with imagery obtained at other times in the growing season (Tottrup 2004). Moreover, to maintain consistency and comparability between the various classifications, we used only one classification method (supervised classification) and one decision rule. Use of other non-parametric or artificial intelligence-based classifiers (e.g. decision trees, self-organizing maps) might also improve the classification accuracy (Lu and Weng 2007). Systematic evaluation of other segmentation methods and parameters would help establish the methodological ‘best practices’ for OBIA-based classification. In addition, the results presented here were obtained with moderate spatial resolution data. The results may or may not be generalizable to classification performed with finer or coarser resolution data. Nevertheless, the results reported here suggest that object-based methods combining spectral and spatial approaches are a potentially important tool in land-use mapping in agricultural landscapes, and perhaps in other types of landscapes as well.

Acknowledgements

This study was made possible by the generous support of the US people through the US Department of Defense, Defense Threat Reduction Agency (DTRA), and Cooperative Biological Engagement Program (CBEP). The contents are the responsibility of the authors and do not necessarily reflect the views of DTRA or the US Government. KLA acknowledges travel support from the Kansas State University Department of Geography and the KSU Graduate School. An earlier version of this manuscript was greatly improved by the comments of two anonymous referees.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work was supported by the Defense Threat Reduction Agency (DTRA) [UP-2 Cooperative Biological Research Project], Department of Defense, USA.

References

Aguirre-Gutiérrez, J., A. C. Seijmonsbergen, and J. F. Duivenvoorden. 2012. "Optimizing Land Cover Classification Accuracy for Change Detection, a Combined Pixel-Based and Object-Based Approach in a Mountainous Area in Mexico." *Applied Geography* 34: 29–37. doi:10.1016/j.apgeog.2011.10.010.

Berlanga-Robles, C. A., and A. Ruiz-Luna. 2002. "Land Use Mapping and Change Detection in the Coastal Zone of Northwest Mexico Using Remote Sensing Techniques." *Journal of Coastal Research* 18: 514–522.

Blaschke, T. 2010. "Object Based Image Analysis for Remote Sensing." *ISPRS Journal of Photogrammetry and Remote Sensing* 65 (1): 2–16. doi:10.1016/j.isprsjprs.2009.06.004.

Blaschke, T., S. Lang, E. Lorup, J. Strobl, and P. Zeil. 2000. "Object-Oriented Image Processing in an Integrated GIS/Remote Sensing Environment and Perspectives for Environmental Applications." *Environmental Information for Planning, Politics and the Public* 2: 555–570.

Castilla, G., and G. J. Hay. 2008. "Image Objects and Geographic Objects" In *Object-Based Image Analysis*, edited by Th. Ïblaschke, S. Lang, and G. J. Hay. Berlin: Springer.

Castillejo-González, I. L., F. López-Granados, A. García-Ferrer, J. M. Peña-Barragán, M. Jurado-Expósito, M. S. de la Orden, and M. González-Audicana. 2009. "Object- and Pixel-Based Analysis for Mapping Crops and Their Agro-Environmental Associated Measures Using QuickBird Imagery." *Computers and Electronics in Agriculture* 68: 207–215. doi:10.1016/j.compag.2009.06.004.

Chang, -C.-C., and C.-J. Lin. 2011. "LIBSVM: A Library for Support Vector Machines." *ACM Transactions on Intelligent Systems and Technology* 2: 1–27. doi:10.1145/1961189.

Clinton, N., A. Holt, J. Scarborough, L. Yan, and P. Gong. 2010. "Accuracy Assessment Measures for Object-Based Image Segmentation Goodness." *Photogrammetric Engineering and Remote Sensing* 76: 289–299. doi:10.14358/PERS.76.3.289.

Comber, A., P. Fisher, and R. Wadsworth. 2005. "What is Land Cover?" *Environment and Planning B: Planning and Design* 32: 199–209. doi:10.1068/b31135.

Cristianini, N., and J. Shawe-Taylor. 2000. *An Introduction to Support Vector Machines and Other Kernel-Based Learning Methods*. Cambridge: Cambridge University Press.

Dickinson, G. C., and M. G. Shaw. 1977. "What Is 'Land Use'?" *Area* 9: 38–42.

Dingle Robertson, L., and D. J. King. 2011. "Comparison of Pixel- and Object-Based Classification in Land-Cover Change Mapping." *International Journal of Remote Sensing* 32: 1505–1529. doi:10.1080/01431160903571791.

Duro, D. C., S. E. Franklin, and M. G. Dubé. 2012. "A Comparison of Pixel-Based and Object-Based Image Analysis with Selected Machine Learning Algorithms for the Classification of Agricultural Landscapes Using SPOT-5 HRG Imagery." *Remote Sensing of Environment* 118: 259–272. doi:10.1016/j.rse.2011.11.020.

Esch, T., A. Metz, M. Marconcini, and M. Keil. 2014. "Combined Use of Multi-Seasonal High and Medium Resolution Satellite Imagery for Parcel-Related Mapping of Cropland and Grassland." *International Journal of Applied Earth Observation and Geoinformation* 28: 230–237. doi:10.1016/j.jag.2013.12.007.

Excelis Visual Information Solutions. 2008. *Feature Extraction Module User's Guide*. Boulder, CO: Excelis Visual Information Solutions.

Fasbender, D., J. Radoux, and P. Bogaert. 2008. "Bayesian Data Fusion for Adaptable Image Pansharpening." *IEEE Transactions on Geoscience and Remote Sensing* 46: 1847–1857. doi:10.1109/TGRS.2008.917131.

Fisher, P. 1997. "The Pixel: A Snare and a Delusion." *International Journal of Remote Sensing* 18: 679–685. doi:10.1080/014311697219015.

Franklin, S. E., and M. A. Wulder. 2002. "Remote Sensing Methods in Medium Spatial Resolution Satellite Data Land Cover Classification of Large Areas." *Progress in Physical Geography* 26: 173–205. doi:10.1191/0309133302pp332ra.

Fung, T., L. L. H. So, Y. Chen, P. Shi, and J. Wang. 2008. "Analysis of Green Space in Chongqing and Nanjing, Cities of China with ASTER Images Using Object-Oriented Image Classification and Landscape Metric Analysis." *International Journal of Remote Sensing* 29: 7159–7180. doi:10.1080/01431160802199868.

Gao, Y., and J. F. Mas. 2008. "A Comparison of the Performance of Pixel-Based and Object-Based Classifications over Images with Various Spatial Resolutions." *Online Journal of Earth Sciences* 2: 27–35.

Heymann, Y., Ch. Steenmans, G. Croiselle, and M. Bossard. 1994. *CORINE Land Cover: Technical Guide*. Luxembourg: Office for Official Publications of the European Communities.

Hosokawa, M., Y. Ito, and T. Hoshi. 1999. "A Remote Sensing Data Classification Method Using Self-Organizing Map." *Geoscience and Remote Sensing Symposium, 1999. IGARSS '99 Proceedings. IEEE 1999 International* 3: 1606–1608.

Hsu, C.-W., -C.-C. Chang, and C.-J. Lin. 2010. "A Practical Guide to Support Vector Machine Classification." http://www.csie.ntu.edu.tw/~cjlin/papers/guide/guide.pdf

Inglada, J., and E. Christophe. 2009. "The Orfeo Toolbox Remote Sensing Image Processing Software." *IGARSS* 4: 733–736.

Keerthi, S. S., and C.-J. Lin. 2003. "Asymptotic Behaviors of Support Vector Machines with Gaussian Kernel." *Neural Computation* 15: 1667–1689. doi:10.1162/089976603321891855.

Koch, D. E., R. L. Mohler, and D. G. Goodin. 2007. "Stratifying Land Use/Land Cover for Spatial Analysis of Disease Ecology and Risk: an Example Using Object-Based Classification Techniques." *Geospatial Health* 2: 15–28. doi:10.4081/gh.2007.251.

Kuemmerle, T., P. Olofsson, O. Chaskovskyy, M. Baumann, K. Ostapowicz, C. E. Woodcock, R. A. Houghton, P. Hostert, W. S. Keeton, and V. C. Radeloff. 2011. "Post-Soviet Farmland Abandonment, Forest Recovery, and Carbon Sequestration in Western Ukraine." *Global Change Biology* 17: 1335–1349. doi:10.1111/gcb.2011.17.issue-3.

Kuemmerle, T., V. C. Radeloff, K. Perzanowski, and P. Hostert. 2006. "Cross-Border Comparison of Land Cover and Landscape Pattern in Eastern Europe Using a Hybrid Classification Technique." *Remote Sensing of Environment* 103: 449–464. doi:10.1016/j.rse.2006.04.015.

Li, M., S. Zang, B. Zhang, S. Li, and C. Wu. 2014. "A Review of Remote Sensing Image Classification Techniques: The Role of Spatio-Contextual Information." *European Journal of Remote Sensing* 47: 389–411. doi:10.5721/EuJRS20144723.

Lu, D., and Q. Weng. 2007. "A Survey of Image Classification Methods and Techniques for Improving Classification Performance." *International Journal of Remote Sensing* 28: 823–870. doi:10.1080/01431160600746456.

Lucas, R., A. Rowlands, A. Brown, S. Keyworth, and P. Bunting. 2007. "Rule-Based Classification of Multi-Temporal Satellite Imagery for Habitat and Agricultural Land Cover Mapping." *ISPRS*

Journal of Photogrammetry and Remote Sensing 62 (3): 165–185. doi:10.1016/j.isprsjprs.2007.03.003.

Miller, D. M., E. J. Kaminsky, and S. Rana. 1995. "Neural Network Classification of Remote-Sensing Data." *Computers & Geosciences* 21: 377–386. doi:10.1016/0098-3004(94)00082-6.

Möller, M., L. Lymburner, and M. Volk. 2007. "The Comparison Index: A Tool for Assessing the Accuracy of Image Segmentation." *International Journal of Applied Earth Observation and Geoinformation* 9: 311–321. doi:10.1016/j.jag.2006.10.002.

Mountrakis, G., J. Im, and C. Ogole. 2011. "Support Vector Machines in Remote Sensing: A Review." *ISPRS Journal of Photogrammetry and Remote Sensing* 66: 247–259. doi:10.1016/j.isprsjprs.2010.11.001.

Navulur, K. 2007. *Multispectral Image Analysis Using the Object-Oriented Paradigm*. Boca Raton, FL: CRC Press.

Peña-Barragán, J. M., M. Ngugi, R. E. Plant, and J. Six. 2011. "Object-based Crop Identification Using Multiple Vegetation Indices, Textural Features and Crop Phenology." *Remote Sensing of Environment* 115–116: 1301–1316.

Petropoulos, G. P., C. Kalaitzidis, and K. P. Vadrevu. 2012. "Support Vector Machines and Object-Based Classification for Obtaining Land-Use/Cover Cartography from Hyperion Hyperspectral Imagery." *Computers & Geosciences* 41: 99–107. doi:10.1016/j.cageo.2011.08.019.

Prishchepov, A. V., V. C. Radeloff, M. Dubinin, and C. Alcantara. 2012. "The Effect of Landsat ETM/ETM+ Image Acquisition Dates on the Detection of Agricultural Land Abandonment in Eastern Europe." *Remote Sensing of Environment* 126: 195–209. doi:10.1016/j.rse.2012.08.017.

Richards, J., and N. Kingsbury. 2014. "Is There a Preferred Classifier for Operational Thematic Mapping?" *IEEE Transactions on Geoscience and Remote Sensing* 52: 2715–2725.

Richards, J. A., and X. Jia. 2006. *Remote Sensing Digital Image Analysis: An Introduction*. 4th ed. Berlin: Springer.

Ruiz, L. A., J. A. Recio, A. Fernández-Sarría, and T. Hermosilla. 2011. "A Feature Extraction Software Tool for Agricultural Object-Based Image Analysis." *Computers and Electronics in Agriculture* 76: 284–296. doi:10.1016/j.compag.2011.02.007.

Ryherd, S., and C. Woodcock. 1996. "Combining Spectral and Texture Data in the Segmentation of Remotely Sensed Images." *Photogrammetric Engineering and Remote Sensing* 62: 181–194.

Stefanski, J., O. Chaskovskyy, and B. Waske. 2014. "Mapping and Monitoring of Land Use Changes in Post-Soviet Western Ukraine Using Remote Sensing Data." *Applied Geography* 55: 155–164. doi:10.1016/j.apgeog.2014.08.003.

Swain, P. H., S. B. Vardeman, and J. C. Tilton. 1981. "Contextual Classification of Multispectral Image Data." *Pattern Recognition* 13: 429–441. doi:10.1016/0031-3203(81)90005-4.

Thomlinson, J. R., P. V. Bolstad, and W. B. Cohen. 1999. "Coordinating Methodologies for Scaling Landcover Classifications from Site-Specific to Global." *Remote Sensing of Environment* 70: 16–28. doi:10.1016/S0034-4257(99)00055-3.

Tomaselli, V., P. Dimopoulos, C. Marangi, A. S. Kallimanis, M. Adamo, C. Tarantino, M. Panitsa, M. Terzi, G. Veronico, F. Lovergine, H. Nagendra, R. Lucas, P. Mairota, S. Mücher, and P. Blonda. 2013. "Translating Land Cover/Land Use Classifications to Habitat Taxonomies for Landscape Monitoring: A Mediterranean Assessment." *Landscape Ecology* 28: 905–930.

Tottrup, C. 2004. "Improving Tropical Forest Mapping Using Multi-Date Landsat TM Data and Pre-Classification Image Smoothing." *International Journal of Remote Sensing* 25 (4): 717–730. doi:10.1080/0143116031000159892б.

Townshend, J., C. Justice, W. Li, C. Gurney, and J. McManus. 1991. "Global Land Cover Classification by Remote Sensing: Present Capabilities and Future Possibilities." *Remote Sensing of Environment* 35: 243–255. doi:10.1016/0034-4257(91)90016-Y.

Townshend, J. R. G. 1992. "Improved Global Data for Land Applications." IGBP Report Number 20, IGBP Secretariat, Stockholm, Sweden.

Unnikrishnan, R., C. Pantofaru, and M. Hebert. 2007. "Toward Objective Evaluation of Image Segmentation Algorithms." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 29: 929–944. doi:10.1109/TPAMI.2007.1046.

Wang, L., and D.-C. He. 1990. "Texture Classification Using Texture Spectrum." *Pattern Recognition* 23: 905–910. doi:10.1016/0031-3203(90)90135-8.

Warner, T. 2011. "Kernel-Based Texture in Remote Sensing Image Classification." *Geography Compass* 5 (10): 781–798. doi:10.1111/j.1749-8198.2011.00451.x.

Wharton, S. W. 1982. “A Contextual Classification Method for Recognizing Land Use Patterns in High Resolution Remotely Sensed Data.” *Pattern Recognition* 15 (4): 317–324. doi:10.1016/0031-3203(82)90034-6.

Xu, M., P. Watanachaturaporn, P. K. Varshney, and M. K. Arora. 2005. “Decision Tree Regression for Soft Classification of Remote Sensing Data.” *Remote Sensing of Environment* 97: 322–336. doi:10.1016/j.rse.2005.05.008.