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Effects of LiDAR-Quickbird fusion on object-oriented classification of mountain resort development

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Abstract. Mountain resort development is having increasing effects on ecological functions in the intermountain West. High-resolution remote sensing has the potential to assist in monitoring this development. We evaluated classification of mountain resort development in the Big Sky, Montana, watershed using Quickbird 2.4-m multispectral imagery with an object-oriented classification. Quickbird imagery, however, has limited spectral resolution; we therefore also evaluated the benefits of fusing Quickbird imagery with LiDAR bare ground and surface model data in an object-oriented approach. Classification accuracies with the fused data increased approximately 1% and were not statistically significantly different based on a 1735 point sample. The classified objects, however, demonstrated more spatial coherency, with more realistically defined shapes and edges.

Keywords: high resolution, multispectral, Montana.

1 INTRODUCTION

Mountain resort development (MRD) is rapidly increasing throughout the intermountain West [1]. MRD generally results in land use and land cover (LULC) change, which can affect ecosystems within the developed area, adjoining undeveloped areas, and downstream and riparian systems. The location of MRD relative to wild and semi-wild areas can have important effects on ecological processes and wildlife diversity [2].

MRD has been found to be spurred by the creation of transportation networks [3], which can negatively affect watershed processes [4,5]. Roads and wilderness trails have been found to affect species composition and increase habitat fragmentation [6,7], which in turn is an important predictor of species distribution and abundance [8].

MRD needs to be accurately mapped in order to assess and monitor its quantity and extent. The use of object-oriented classification and analysis of high-resolution imagery is advantageous for mapping land use/land cover (LULC) associated with MRD. High-resolution imagery provides a detailed view of the land's surface and is important for mapping local areas [9]. Traditional pixel-based classification of high-resolution imagery has been difficult due the lack of spectral depth of most high-resolution sensors and high spatial heterogeneity of the imaged scene [10,11]. Object-oriented classification and analysis can overcome pixel-based classification limitations by allowing users to classify based on contextual information extracted from an image in addition to spectral characteristics [12]. Many recent studies have investigated the use of object-oriented analysis for LULC classification, including, for example, distinguishing burned and shadowed areas [13], monitoring vegetation changes in the southwestern United States [14], and identifying woody vegetation in urban areas [15].

Image fusion might also increase the accuracy of object-oriented classification and analysis. The purpose of image fusion is to combine information from different sensors in order to increase the information extracted [16]. The fusion of LiDAR and multispectral images has been shown to increase the accuracy of forest parameter estimations as compared

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to single sensors [17,18], map vegetation species composition and distribution [19], and extract buildings and trees from urban environments [20].

Our objective was to evaluate the utility of high-spatial-resolution imagery fused with LiDAR data to map LULC associated with MRD using object-oriented analysis. Results were compared with object-oriented analysis in the absence of LiDAR data.

2 METHODS

Our study was the West Fork of the Gallatin River watershed near Big Sky, Montana, including a 0.5-km buffer around the watershed (Fig. 1). Big Sky is surrounded by the Gallatin National Forest in southwestern Montana and is located within the Greater Yellowstone Ecosystem [21]. Elevation ranges more than 2000 m and is an important predictor of climate and vegetation species distribution [21]. Vegetation is composed of coniferous forests, shrublands, and grasslands. Frost free days range from 60-90 and decrease with increased altitude [21,22].

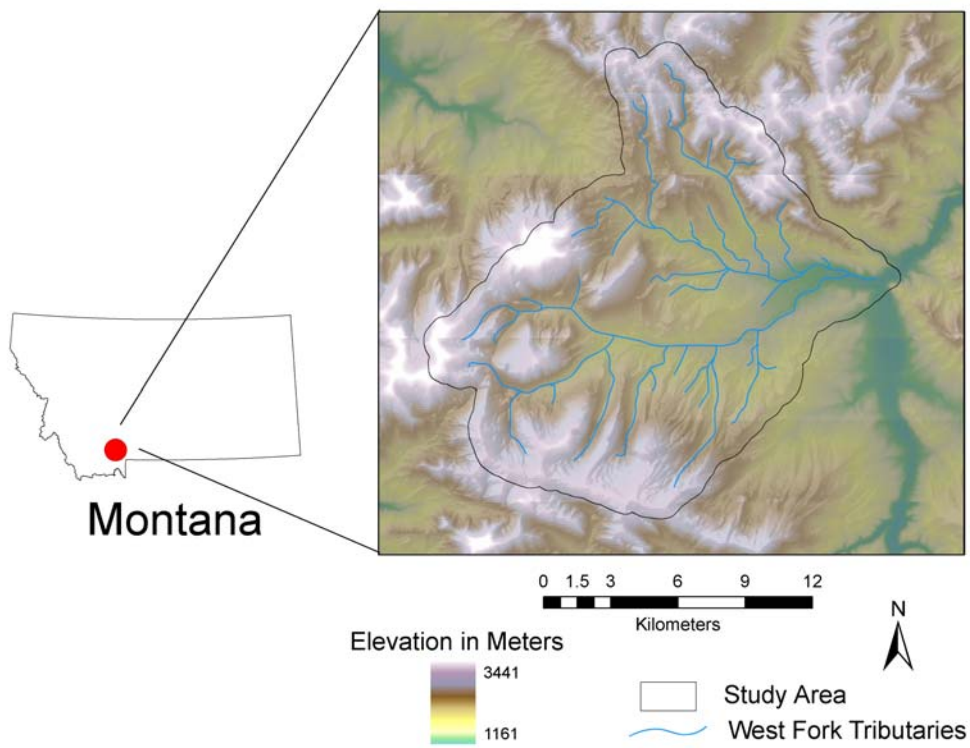

Fig. 1. Study area, showing the Big Sky, Montana, watershed, consisting of the West Fork of the Gallatin River.

Imagery used included an 11-tile Quickbird image with 2.4-m spatial resolution. A tile represents the 16.5 km x 16.5 km footprint of the sensor containing only the portion of the scene related to the study area with all outlying areas containing no data. The Quickbird image contained 4 bands in the visible and near infrared (NIR) portion of the electromagnetic spectrum including blue (450-520 nm), green (520-600 nm), red (630-690 nm), and NIR (760-900 nm). The 11 tiles were mosiacked to create one master image.

1-m airborne laser swath mapping, herein referred to as LiDAR, bare earth and surface models created from point clouds were also used. The bare earth model was created through triangulation of the last returns in a 55-m window. The surface model was created using a linear Kriging algorithm to interpolate first returns in a 5-m window. The surface model represented surface land cover, such as the top of tree canopies and the roofs of buildings. The bare earth model estimated elevation with all land cover (e.g., vegetation and buildings) removed. The LiDAR images were resampled to 2 m using nearest neighbor resampling. All images were acquired in the summer of 2005 and registered to a UTM NAD 83 Zone 12 projection with an RMSE of 0.06.

The original 11 tiles of Quickbird imagery were used to create a six image subset. Subsetting was necessary due to data processing limitations within the object-oriented software. The six subsets were then used to create matching subsets of the resampled LiDAR bare earth and surface models. The subsets were individually imported into the Definiens Professional 5: Large Data Handling (LDH) software [23]. The Quickbird and LiDAR fused data created data sets with multispectral, bare-earth elevation, and surface information for each pixel.

The subsets were initially segmented using a Multi-Resolution Segmentation (MRS) algorithm [23]. Separate segmentations were created for each subset with and without LiDAR data. The MRS algorithm is a heuristically applied algorithm that creates objects by minimizing internal object heterogeneity. Object heterogeneity is calculated as a weighted average across all input bands with the total weight summing to one. Object heterogeneity is controlled by selecting an arbitrary scale factor, which determines the amount of heterogeneity acceptable and is resolution dependant. The scale factor required to create objects for individual houses will be different than the scale factor required to create objects representing a neighborhood or subdivision, for example. The appropriate object is one that is "as large as possible and as fine as necessary" and thus will vary depending on the desired output [23]. The segmentation process resulted in vector based "objects" with attributes corresponding to the mean and standard deviation values of the pixels within the object for each input layer. Additional contextual metrics can then calculated and used in the classification process. The appropriate MRS was determined if objects borders did not overlap different LULC classes by visual inspection.

The creation of objects is also influenced by weighting layer pixel values and spatial homogeneity. The default was a pixel value weight of 0.9 and a spatial weight of 0.1 [23]. A decrease in pixel input value weight and a corresponding increase in spatial weight results in objects with less similarity in their pixel values. The default spectral and spatial weights were chosen because they provided objects that followed spectral contrast lines for different land cover by visual inspection.

A Spectral Difference Segmentation (SDS) was performed after the appropriate MRS was identified [23]. SDS is a merging algorithm designed to merge spectrally similar objects produced in previous segmentations. Objects were merged if their standard deviation was below a user defined threshold. The threshold is used to determine the amount of object aggregation. The appropriate SDS was identified if most or all adjacent objects were merged without creating mixed land cover objects. This resulted in larger objects, which were more semantically meaningful.

The classification scheme was developed based on common MRD cover types and included roads, buildings, rock, bare soil, golf course, non-treed vegetation, lakes/ponds, sewer ponds, shadow, snow trees, and rivers/streams. This study was part of a larger study examining the effect of MRD on stream nitrogen levels, which required distinguishing isolated waste water holding ponds and golf courses. These types were manually digitized at the end of the classification process.

Classification of objects was conducted using the nearest neighbor (NN) algorithm in Definiens Professional. The NN algorithm classifies objects based on user identified sample objects utilizing user selected metrics. Metric selection, which increases efficiency, was determined using Definiens' Feature Space Optimization tool (FSO). FSO works by examining any number of input variables and identifying the variables that contain the greatest distance between samples to be applied to the NN classifier.

The following pixel derived metrics were selected by FSO: object mean and standard deviation of all input bands excluding blue (green, red, NIR, NDVI, surface, and bare earth). NDVI is a commonly used vegetation index that is calculated as (NIR-red)/(NIR+red) [24]. NDVI is a unitless measure with a positive correlation to vegetation amount or health. The following contextual metrics were used: length/width, asymmetry, density, compactness, and rectangular fit.

Training samples were chosen by selecting objects in each image that represented their class. Definiens Professional allowed the sample metrics collected in one image to be applied to subsequent images. This allowed the sample metrics collected in the first subset to be applied in the classification of subsequent subsets. Once all 12 subsets were classified, they were mosaicked to create two final classifications, a Quickbird classification and a fused LiDAR and Quickbird classification.

The fused classification required additional post processing due to missing data values within the LiDAR image. This was overcome by applying the Quickbird classified values to the missing data.

The vector based classification was converted to a raster image with 2.4-m pixel resolution to retain the spatial properties of the original Quickbird data. A total of 1126 accuracy assessment points were generated using a stratified random sample from the Quickbird classification. An additional 609 stratified random sample points were obtained from the fused classification. The two sets of points were merged and used to assess the accuracy of both classifications. Producer's and user's accuracies for each class and the Kappa statistics were calculated for each classification [25]. Overall accuracy was calculated using the methods outlined in Carrao et al., 2007 [26]. This method differs from the traditional overall accuracy, in that it is calculated based on the relative proportion of each class to the total number of classified pixels.

3 RESULTS

The overall accuracy for the Quickbird classification was 90% with a Kappa statistic of 0.76 (Table 1). The bare soil class had low user's and producer's accuracy and was often confused with impervious surfaces. Grass had a high error of commission rate with 35% and was often confused with impervious surfaces and trees. The river, shadow, and snow classes each preformed similarly with a low producer's accuracy and high user's accuracy. The building class had a low error of commission as seen in the high user's accuracy but also had higher error of omission as seen in the low producer's accuracy. The road class had a higher error of commission than omission. The rock class had a high error of commission with 35% and a moderate error of omission with 11%.

The fused classification had an overall accuracy of 91% and a Kappa statistic of 0.78 (Table 2). Bare soil had had similar error rates to the Quickbird classification (Table 2). The error of omission for bare soil, however, increased over the Quickbird classification. All other individual user's and producer's accuracy were generally higher than the Quickbird classification resulting in reduced errors of omission and commission. The building class improved substantially compared to the Quickbird classification, with a 16% decreases in error of omission and a slight 1% decrease in error of commission. The road class had a 5% decrease in error of commission with the fused classification and no increase in the error of omission. The rock class had slight decreases in both errors of omission and commission than in the Quickbird classification.

Table 2. Error matrix for Quickbird classification.

		Reference Data											
		Bare Soil	Building	Grass	Lake	River	Road	Rock	Shadow	Snow	Tree	**TOTALS**	User's Accuracy
Map Data	Bare Soil	35	1	2	0	0	10	1	0	0	4	53	66%
	Building	0	131	0	0	0	4	1	0	0	0	136	96%
	Grass	45	11	168	1	1	12	9	0	0	12	258	86%
	Lake	0	0	0	47	1	0	1	0	0	0	49	94%
	River	0	0	0	0	17	0	0	0	0	0	17	100%
	Road	20	48	0	0	0	202	3	0	0	1	274	74%
	Rock	19	5	8	0	0	13	181	12	30	7	275	66%
	Shadow	0	0	0	0	0	0	0	52	0	0	52	100%
	Snow	2	1	0	1	0	0	2	0	73	2	81	90%
	Tree	6	19	11	4	6	7	5	5	2	474	539	88%
	TOTALS	127	216	189	53	25	248	203	69	105	500	1735	
	Producer's Accuracy	28%	61%	89%	88%	68%	81%	89%	75%	70%	95%		

Overall Classification Accuracy = 90%　　　Overall Kappa Statistics = 0.76

The classifications were compared in order to determine if there was any statistical difference between the two classifications. We were not able to detect any statistical differences in Kappa statistics based on our sample of 1735 points [25]. The z statistic was 1.06 (p-values = 0.02), below the critical value of 1.96 at an alpha of 0.05.

4 DISCUSSION

4.1 Object Segmentation

The segmentation process was successful in the creation of semantically meaningful objects. Houses were easily identified in both segmentations and generally resulted in independent objects. This allowed contextual information in addition to spectral and elevation information to be used in classification. The key for the segmentation process was the creation of homogeneous objects. This was achieved through the heuristic nature and application of the MRS and SDS segmentation algorithms. The results were objects that represented their land cover class spectrally and contextually.

Table 3. Error matrix for fused Quickbird/LiDAR classification.

		Reference Data											
		Bare Soil	Building	Grass	Lake	River	Road	Rock	Shadow	Snow	Tree	**TOTALS**	User's Accuracy
Map Data	Bare Soil	19	1	0	0	0	1	0	0	0	0	21	90%
	Building	1	166	0	2	0	4	0	0	0	0	173	96%
	Grass	45	12	172	10	0	18	7	0	4	19	287	87%
	Lake	0	0	0	37	1	0	1	0	0	0	39	94%
	River	0	0	0	0	19	0	0	0	0	0	19	100%
	Road	24	27	0	1	0	202	1	0	1	0	256	79%
	Rock	32	4	5	0	0	20	184	2	13	10	270	68%
	Shadow	0	0	0	2	1	0	0	62	0	0	65	97%
	Snow	2	1	1	0	0	0	5	0	86	2	97	89%
	Tree	4	5	11	1	4	3	5	5	1	469	508	93%
	TOTALS	127	216	189	53	25	248	203	69	105	500	1735	
	Producer's Accuracy	15%	77%	91%	90%	84%	81%	91%	90%	82%	94%		

Overall Classification Accuracy = 91% Overall Kappa Statistics = 0.78

The use of LiDAR resulted in objects that appeared to better reflect surface features compared to using Quickbird imagery alone (Fig. 2). The addition of elevation information in the fused classification resulted in many more objects than the Quickbird classification. This allowed objects to have a much more distinguishable shape and helped avoid situations where separate objects were spatially merged. Dense housing, for example, in the Quickbird classification was block shaped, while the same area in the fused classification had individual houses that were shaped similar to their architecture (Fig. 2).

The issue of scale presented a problem for the segmentation process. Previous studies have focused on the use of homogenous landscape regions such as primarily urban or natural areas [14,15,27,28]. These studies have shown the successful use of object-oriented classification and analysis, but have not explored the use for heterogeneous landscapes. There were two major land cover types within our study area, developed and undeveloped. Developed consisted of road networks and buildings. Undeveloped consisted of grassland, river/stream, lake/pond, and forested areas. These types have different levels of appropriate segmentation. The appropriate level of segmentation to create an object representing a house will be smaller than the level needed for forests or grass lands. An intermediate segmentation scale was used as a compromise in order to create objects "as large as possible and as fine as necessary" [23].

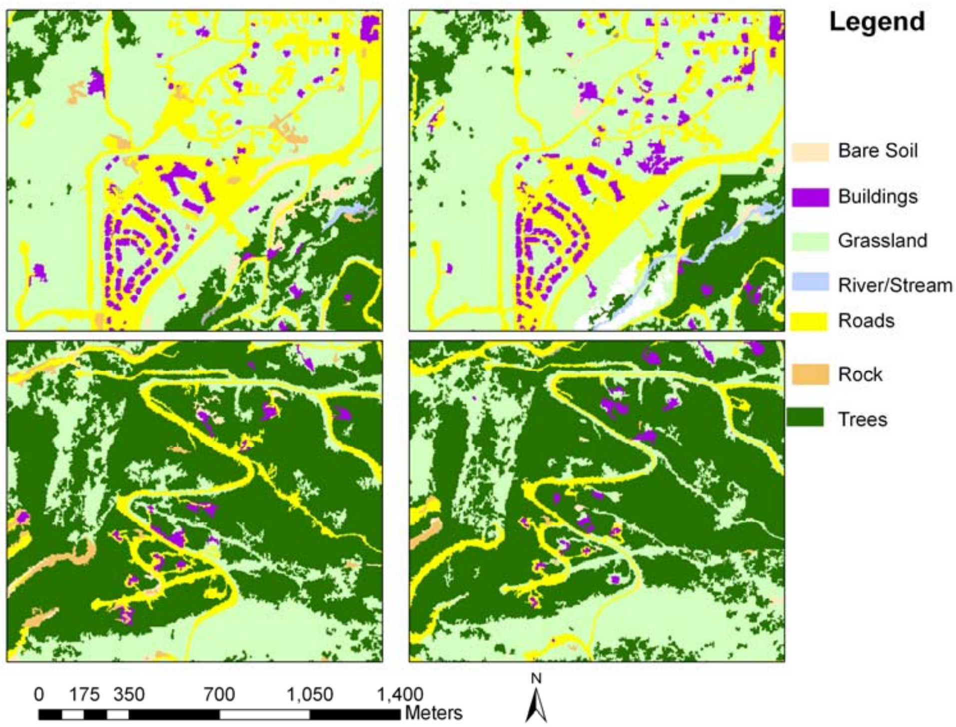

Fig. 2. Example of Quickbird classification on the left and fused Quickbird/LiDAR classification on the right. The fused classification shows more spatially distinct and realistic object boundaries with, for example, buildings that are more separated and rectangular and roads of more even width.

Mixed land cover objects caused difficulty in the selection of class samples. Samples that represented their class while still capturing the variability of their class were selected. This required the selection of some mixed land cover objects as samples of the dominant land cover they contained. The spectral attributes of an object were the means of all pixels it comprised for each input. Mixed land cover objects, therefore, skew the distribution of the response for the dominate land cover they represent. This is a likely explanation misclassification rates (Fig. 3). Objects that were predominately impervious also tended to have small patches of vegetation, for example.

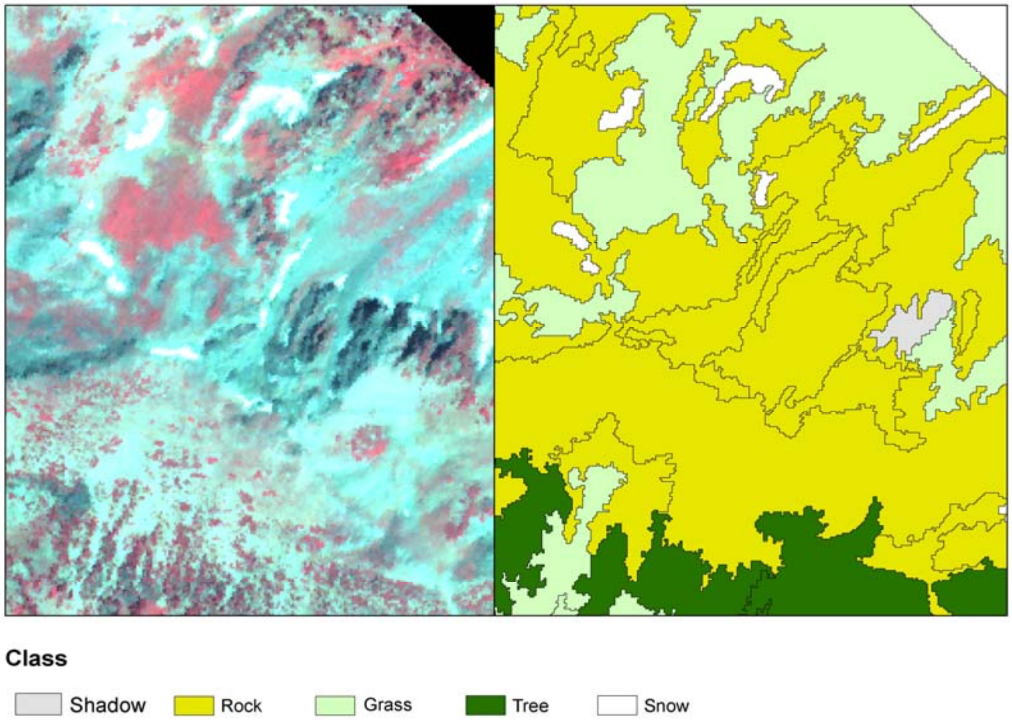

Fig. 3. Comparison of Quickbird image and fused classifications showing mixed land cover objects and how they were discretely segmented.

Point based accuracy assessment does not account for mixed land cover objects. Thus true accuracy is unknown. Point based accuracy only accounts for what is on the ground at one particular point. Points located on the edges of objects or part of mixed land cover objects could inflate error rates and lead lower accuracies.

Transition zones created issues in both classifications. Bare earth and grass are not discrete land cover types, for example. They often flow between each other with varying intensity. This caused difficulty with the creation of distinct boundaries and resulted in the low accuracy for the bare soil class.

The object-oriented software was memory intensive and had data processing limitations. High-spatial-resolution images contain large numbers of pixels for small areas. The Quickbird full image was 64 MB and the LiDAR image was 1.7 GB. The software used could not handle the file sizes and therefore required subsetting the data and resampling the LiDAR data. This created objects that did not always flow between subsets (Fig. 4). A study that mapped benthic habitat on the gulf coast of Texas also needed to resample 1-m aerial photographs and subset the study into several smaller portions [29]. Other studies have focused on the use of small, less computationally demanding areas [12,14,15,27,28].

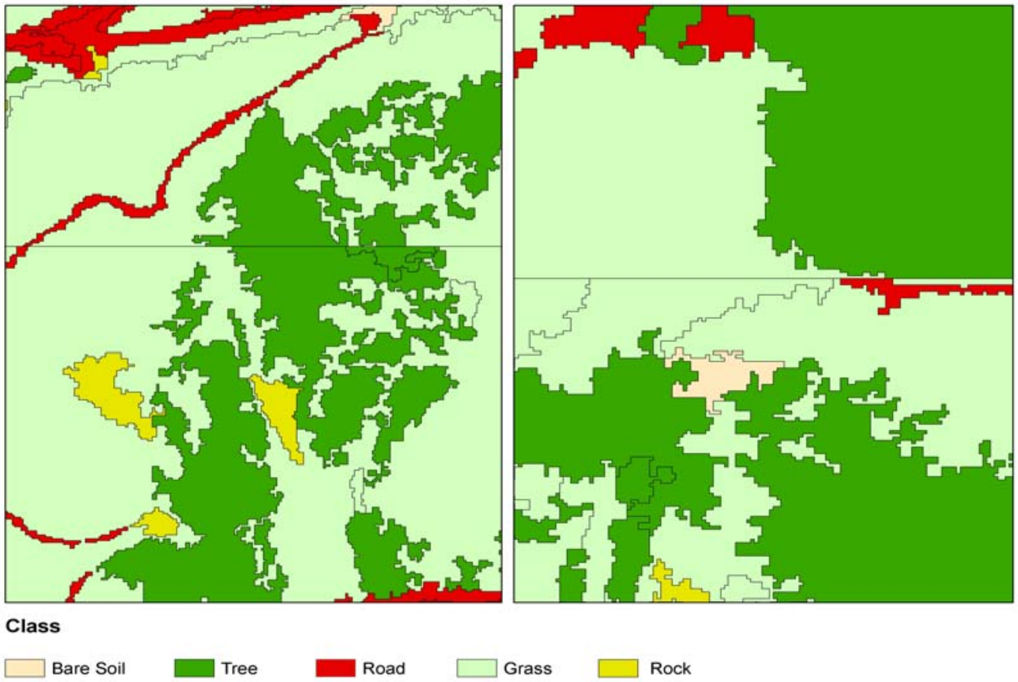

Fig. 4. Fused classification showing effects of subsetting images due to memory limitations.

4.2 The Quickbird Classification

Overall accuracy for the Quickbird classification was high at 90%. Previous studies have found the lack of spectral depth of high-resolution sensor make pixel based classification difficult [9]. Classes such as roads, shadows, and water bodies have had high misclassification rates with traditional pixel-based classification [9,30]. Object-oriented classification in our study was able to overcome this through the addition of the contextual metrics to the classification process. This can be seen in the low amount of confusion among the three classes.

The Quickbird classification had problems with several classes. The bare ground class, for example, was often misclassified as an impervious surface or grass. This was a result of the continuous nature of bare soil and the creation of discrete boundaries. Small patches of bare soil were often contained in larger objects of impervious surface or grass. The impervious surface classes were also confused with forest and grass. Similar to the bare ground class, misclassification can be attributed to small patches not being identified.

Previous studies on the use of object-oriented classification have found similar results. One study mapped densely populated areas of Santa Barbara, California with an overall accuracy of 79% [30]. Another study mapped an area of mixed residential and agriculture land cover with an overall accuracy of 74% [31]. Both studies found that roads or building classes had confusion [30,31]. This was mostly a result of the two classes not being separated in the segmentation process, as seen in our classification. Our classification had confusion with bare soil and grass. This was overcome in one study by the use of broad classes such as non-photosynthetic vegetation/bare soil and general vegetation [30].

4.3 The Fused Classification

The accuracy of the fused classification was slightly higher than the Quickbird classification, but no statistically significant differences were found. The additional information resulted in the segmentation creating objects that better reflect surface objects by adding contrast in areas of spectrally low contrast (Fig. 5). This can be seen in the creation of objects representing small groups of trees and small patches of bare soil. The Kappa statistic did not have a statistically significant increase, but the estimated overall accuracy and Kappa statistic were higher. This is consistent with our observations that the differences were represented by more accurate delineation of objects, although the total area affected by these differences was small, thus not significantly affecting classification accuracy. Individual class user's and producer's accuracy also improved for many of the classes, thus reducing the error of commission and omission.

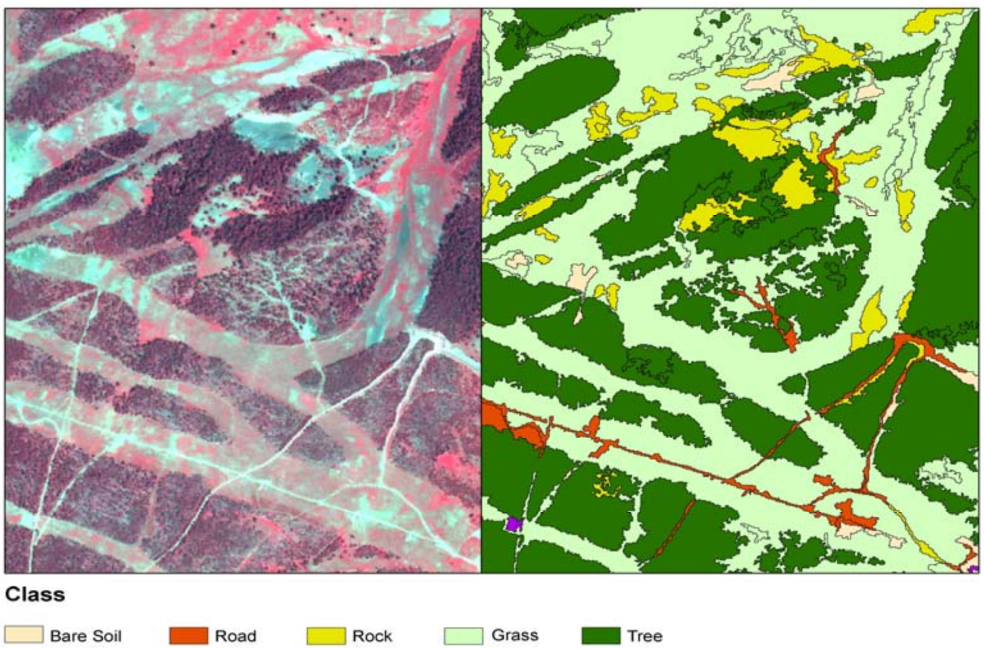

Fig. 5. The addition of LiDAR information resulted in the segmentation creating objects that better reflected surface objects by adding contrast in areas of spectrally low contrast, as demonstrated in this mixed land cover area.

The fused classification had similar accuracy issues as the Quickbird. Bare soil had a high rate of misclassification with impervious surfaces and grass. Impervious surfaces had a high confusion with grass. Snow also had a high misclassification rate with impervious surfaces. These errors can be attributed to the creation of discrete boundaries for continuous land cover types. Overall, the classification had higher consistency, as there were less dramatic differences between the user's and producer's accuracies than seen in the Quickbird classification.

Previous studies have used image fusion with topographic data with great success. Studies have compared image fusion to single sensors and found fusion results in increased accuracy for pixel-based classifications due to the inclusion of elevation information to the classification process [17,18,19]. Our results show little improvement in overall accuracy when compared with the Quickbird classification. This is a result of the success and power of the segmentation processing in creating objects, which can be accurately classified through the addition of contextual metrics. The addition of the LiDAR resulted in finer objects, which significantly reduced error rates but did not improve overall accuracy.

5 CONCLUSION

Object-oriented analysis and classification works well with high-resolution imagery. Object-oriented classification can overcome the traditional spectral limitations of high-resolution sensors. The appropriate segmentation level coupled with the addition of contextual metrics can accurately create detailed LULC maps. Object-oriented classification can be used to map accurately heterogeneous land cover areas such as dense urban areas, rural or suburban areas, and natural land cover.

Image fusion and object-oriented classification created more realistic objects. This resulted in a classification that was more visually appealing. This is advantageous if spatial precision required, but might not be necessary if only point-based accuracy is needed.

There are a plethora of future research opportunities for object-oriented classification and analysis. One significant research area includes identification of an appropriate spatial resolution for use with object-oriented classification and analysis. Quickbird imagery has high spatial resolution but is still plagued by pixilation, which blurs the boundaries of different land cover. Increased class accuracy and homogenous objects might be achieved if the optimum spatial resolution was identified.

Another research area would be full utilization of contextual metrics. Definiens software allows for an extreme number of metrics including standard deviations and ratios of both spectral and contextual metrics to be calculated. This is a new frontier in image classification, as most of these have not be tested for relevance or relation to different LULC classes. These new metrics need to be researched and identified in order to streamline classification of objects.

Object-oriented software also needs to be programmed so as to make full use of the today's high resolution data. Today's technology is resulting in an increased number of sensors with increasing spatial resolution that require matching data handling capabilities.

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