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Abstract. Documenting patterns of land use and land-cover change in mountain resort development (MRD) is important for understanding the effects of these changes of fragile mountain environments. High-spatial-resolution imagery can be useful for mapping MRD, but lack of a long-term record of such imagery hampers our ability to analyze temporal patterns. We use the results from classification of high-spatial-resolution imagery (Quickbird and LiDAR) to calibrate concurrent moderate-resolution imagery (Landsat). We then use historical moderate-resolution imagery to analyze changes in spatial patterns of MRD over time. Analyses revealed that increases in MRD occurred disproportionately close to streams, which raises concerns for impacts on water quality. [DOI: 10.1117/1.3615998]

Keywords: multispectral; multiresolution; NDVI image differencing; spatial analysis; change detection; boosted classification trees.

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1 Introduction

Mountain resort development (MRD) is rapidly increasing throughout the intermountain west. The result is change in land use and land cover (LULC), which can affect ecosystems within the developed area, adjoining undeveloped areas, and downstream and riparian systems.

The conversion of naturally vegetated land to impervious surfaces, such as roads, can have dramatic affects. Roads have been found to increase habitat fragmentation.[1] Habitat fragmentation in turn has been found to decrease species composition distribution and abundance.[2–4] Roads also affect physical processes. Roads have been shown to increase drainage density and sediment production due to erosion and deposition.[5,6]

Understanding the causes of LULC change from MRD is important in order to mitigate its effects. Accessibility has been touted as a primary growth factor for tourism in mountain areas.[7] We would expect, therefore, that MRD would be correlated to roads within a watershed. Other studies have shown that the quality of life associated with living near areas rich with natural amenities is a significant attraction.[8,9] Amenity development often results in the conversion of rural land to residential land for "ranchette" type development.[2,10] Topography and water area have been considered important variables for the basis of a "natural amenity index."[11] It also is important to evaluate MRD with respect to topographic variables because, for example, increased development on steeper slopes might increase rates of erosion and related impacts of aquatic ecosystems.[6,12]

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Remote sensing has the potential to be a valuable tool for analyzing MRD and changes in LULC over time. The use of remote sensing for identification of LULC change has been well documented.[13] Change detection algorithms are as numerous as possible applications and vary in complexity.

Many studies have compared the accuracy and effectiveness of various change detection methods. Univariate image differencing has been recommended for binary change/nonchange identification.[13,14] The use of vegetation indexes for change detection also has been shown to be advantageous over single band analysis because it reduces data volume and captures information not available in any single band.[13] Normalized Difference Vegetation Index (NDVI) image differencing has been shown to be advantageous over the use of other vegetation indexes for identification of deforestation and vegetation loss and has also been shown to be less affected than some other indexes by topographic relief.[15] This makes NDVI image differencing an ideal candidate for binary change/no-change identification related to MRD, where the clearing of natural habitats for anthropogenic development in an area of high relief is the type of change with which we are concerned.

Classification of from-to change is imperative, once change has been identified, in order to discern development patterns. Classification tree (CT) methods are becoming increasingly popular for classification of remotely sensed data and might be useful for such from-to change. CTs have been shown to create more accurate classifications than other methods.[16] CTs offer the advantages of being nonparametric, working equally well with continuous and nominal data types, producing interpretable rule sets, and handling noisy data sets.[17] CT, therefore, offers significant advantages over other classification methods; however, it can be negatively affected by the presence of outliers in training data and by unbalanced data sets.[18] The use of statistical boosting has been shown to significantly increase the accuracy of CTs.[18–21]

Multiresolution image classification has been shown to increase single image classification accuracy[22–24] and is generally considered a form of image fusion whose purpose is to combine information from different sensors in order to increase the information extracted.[25] The use of images with varying resolutions for change-detection purposes, however, does not seem to be as well developed as use for single classifications. This raises a significant issue with modern high-resolution satellite imagery. High-resolution imagery is increasingly being used for LULC classifications, but the absence of a long-term archive of high-resolution imagery, as exits for moderate-resolution imagery, has made it less useful for LULC change analysis. Development of approaches that combine high-resolution classifications with moderate-resolution imagery for LULC change analysis would greatly increase the usefulness of high-resolution classifications.

The purpose of this study was to (*i*) identify LULC change related to MRD in Big Sky, Montana, between the dates of July 2005 and July 1990 using high-resolution imagery from 2005 and moderate-resolution imagery from 2005 and 1990, and (*ii*) evaluate topographical variables and spatial relationships to roads and streams as possible correlates of MRD in the area.

2 Methods

2.1 Study Area

The study area for this project was the West Fork of the Gallatin River watershed near Big Sky, Montana (Fig. 1). Big Sky is surrounded by the Gallatin National Forest in southwestern Montana and located within the Greater Yellowstone Ecosystem.[26] The range of elevation is >2000 m and is an important predictor of climate and vegetation species distribution.[26] Vegetation is composed of coniferous forests, shrublands, and grasslands. Frost-free days range from 60 to 90 and decrease with increased altitude.[26,27]

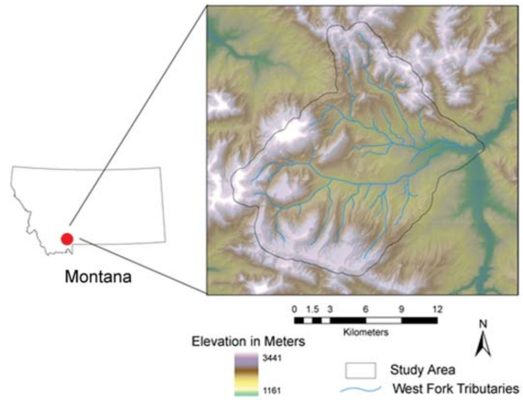

Fig. 1 Location of West Fork of Gallatin River watershed study area to state of Montana.

2.2 Summary of Methods

Identification of change patterns for statistical analysis was a multistep process. First, a 2005 classification with high accuracy (91%) based on a combination of Quickbird and LiDAR imagery was resampled from 2.4 to 30 m to match Landsat image resolution. Second, two normalized near-anniversary-date Landsat 5 images were converted to NDVI and differenced to identify change from no-change. This enabled us to determine which areas in the 1990 image needed to be classified, while the remainder of the study area could be assumed to have the same classes in 1990 as they did in 2005. The potentially changed locations in the 1990 Landsat image were classified, using the unchanged locations as training. Changed areas were then combined with the unchanged locations in the 2005 classification to create the final 1990 classification. The spatial distribution of change was analyzed through a combination of descriptive statistics and CT.

2.3 Preprocessing

Landsat 5 Thematic Mapper (TM) images (path 39 and row 28) from July 12, 2005 and July 3, 1990 were obtained from the EROS Data Center with level-one terrain correction. The two scenes were geometrically registered to a July 2005 Quickbird image and set to a UTM NAD 83 Zone 12 projection to ensure all data used in the analysis were geometrically co-locatable. The Landsat 1990 image had a root-mean-square error (RMSE) of 0.05 pixels and the 2005 image had a RMSE 0.07 pixels. The full scenes were then subset to the study area.

Data transformations were performed on both Landsat dates to provide derived indexes for use in the classification and change-detection processes. A tasseled cap (TC) transformation was performed, resulting in three new bands representing relative soil brightness, relative amount of green vegetation, and relative soil moisture content.[28] NDVI was also calculated as (NIR-red)/(NIR+red).[29]

A multidate image normalization using linear regression was used as a radiometric normalization procedure on the 1990 and 2005 NDVI images.[30] The 2005 image was selected as the independent variable, and the 1990 image was selected as the response variable. pseudo-invariant features representing features that were presumed to have not changed over time were identified and selected. Stable anthropogenic features included features that were both bright (e.g., buildings) and dark (e.g., man-made water features) and were ideal candidates; an attempt was made to select features in relatively flat areas so as not to introduce topographic effects. A total of 224 points were collected; 100 points were randomly selected and set aside to be used as a validation data set. The R^2 for the NDVI regression model was 0.91 and shown to be statistically significant (p-values of <0.001). Paired t-testing was performed in order to determine whether the normalization improved the 1990 image radiometric match to the 2005 image. It was determined that the mean difference between the 2005 and 1990 images was 7.357 with a standard deviation of 17.186. The mean difference between the 2005 and the normalized 1990 image was 6.126 with a standard deviation of 9.27. The paired t-test indicated that there was a difference between both the 1990 image and the 1990 normalized image and the 2005 image. This difference was decreased, however, with the normalization process.

2.4 Change Detection

NDVI image differencing was used for binary change/no-change identification. Image differencing was performed by subtracting the pixel values of the 2005 NDVI image from the normalized NDVI 1990 image. The resulting values have no-change centered on the mode and areas of change located in the tails of the distribution. Change was then identified by defining a threshold based on knowledge of certain changed locations to separate areas of change from no change. The appropriate threshold was identified so as to include all areas of change while minimizing false-positive change identification. A binary image of change and no change was created based on this threshold.

A 30-m resolution 2005 classification was created based on a classified fused Quickbird and LiDAR classification with a resolution of 2.4 m.[31] The Quickbird/LiDAR classified image included ten land-cover classes, was created using an object-oriented classifier, covered the entire study area, and had an accuracy of 91%. The original classes of grasslands/shrublands, bare soil, and golf courses were generalized to grasslands/shrublands. Houses, roads, and rock were generalized to impervious surfaces. Lakes, rivers, ponds, streams, and wastewater holding ponds were generalized to water. The forest class was maintained as forest. Snow and shadows were left to represent themselves. The generalized 2.4-m classification was then resampled to 30 m to match the Landsat images. Resampling was accomplished by determining within each 30-m pixel the most common land-cover type present.

The use of the resampled generalized classification resulted in 30-m pixels that represented mixed land cover. This resulted in the loss of important information related to MRD, such as roads and other smaller features. A percent impervious model was created in order to overcome this loss of information by determining within each 30-m pixel the percent of 2.4-m pixels that were impervious, based on the 2.4-m classification. Pixels that were 20% or more impervious were reclassified as impervious for the 30-m classification, a level selected to be consistent with a concurrent study being conducted in the watershed. This resulted in an overestimation of the impervious class based solely on pixel areas but also decreased our loss of information related to MRD due to resampling.

The NDVI-based change/no-change image was used to create two images with areas masked for changed and no-change locations, respectively, from the 1990 Landsat image. Areas of no change were therefore assigned the same classes as in the 2005 classification and were used as training for classification of the changed locations. Data used for the 1990 classification consisted of normalized data from all six Landsat reflective bands and derived indexes (NDVI and TC). The See5 data-mining program[32] was used for classification. See5 is a statistical data mining software package that performs CT analysis with boosting. A total of 10 boosts were used. The unchanged 2005 classified pixels were merged with the classified changed 1990 pixels to create a final 1990 classified map.

2.5 Accuracy Assessment

Accuracy for the 1990 classification was assessed using a stratified random sampling design. A total of 302 sampling points were acquired. An additional 14 points were manually identified because the stratified random design was unable to identify an acceptable number of water

Table 1 Table of classification scheme for years 1990, 2005, and change image.

Classified as in 1990	Classified as in 2005	Change class
Forests	Impervious surfaces	FI
Grasslands/shrublands	Impervious surfaces	GI
Forests	Grasslands/shrublands	FG

points. These were then combined with the stratified random points for a total of 316. These points were then compared to 1:40,000-scale 1990 aerial photographs from the National Aerial Photography Program archives.

Producer's and user's accuracies for each class and the Kappa statistics were calculated for each classification.[33] Overall accuracy was calculated using the methods outlined in Ref. 34. 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.

2.6 Change Pattern Analysis

Our data set contained the full population of possible land-cover change for our study area. This allowed descriptive statistics to be examined in order to evaluate potential indicators of change in the study area. Four potential indicators were identified: slope, aspect, distance-to-roads, and distance-to-streams. There were 16 theoretically possible from-to change classes. Three of the 16 were identified as possibly being related to MRD (Table 1). These were individually coded so as to separate the different types of change for spatial pattern analysis. Two of the classes represent change from natural habitats to human habitats through the conversion of vegetation to impervious surfaces. FI represented change from forests in 1990 to impervious surfaces 2005. GI represented change from grasslands/shrublands in 1990 to impervious surfaces in 2005. FG represented changes in forests in 1990 to grasslands/shrublands in 2005. A national forest boundary map created by the U.S. Forest Service was used to exclude areas on forest service land, where MRD was known not to have occurred.

Slope and aspect were calculated from a 1-m LiDAR digital elevation model resampled to 30 m using the nearest-neighbor algorithm. Slope was calculated as degrees, and aspect was calculated as a categorical variable representing eight different directions (north, northeast, east, southeast, south, southwest, west, and northwest) and flat. A distance-to-roads layer was created by calculating distance from a road vector file of the area onto a 30-m grid. The road layer was created by GIS Department of Gallatin County, Montana, and contained all the roads in the study area. This layer is updated twice yearly by Gallatin County and was current as of January 2008. Distance to streams represented distance on a 30-m grid from streams identified by using a multiple flow direction algorithm on a 10-m parsed elevation model created from the original 1-m LiDAR elevation model. The 10-m parsed elevation model was created by selecting every 10th point on the 1-m LiDAR model and rescaling to 10 m.

Descriptive statistics were computed relating each type of change to each indicator variable being evaluated. The mean and standard deviation of each type of change for each variable was calculated and compared to the mean and standard deviation of land-cover types and variables for the 1990 classification.

CT was used to determine the relative relationship of the potential indicators to the three different types of change. The three change classes were used as the response variables. Slope, aspect, distance-to-streams, and distance-to-roads were used as the explanatory variables. Standard cross-validation methods were used to avoid overfitting the CTs.[35]

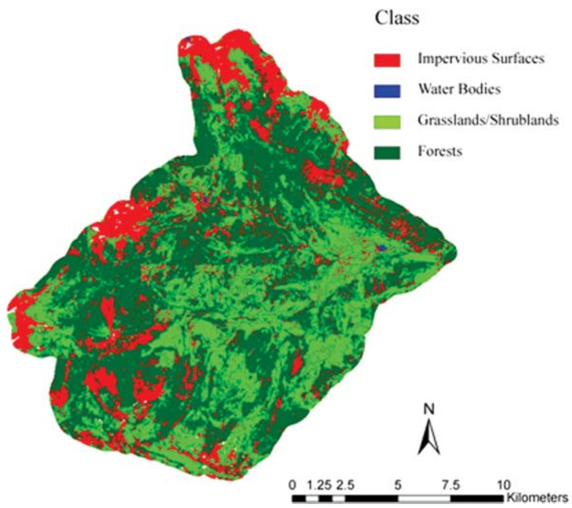

Fig. 2 Classified 1990 Landsat TM image developed using 2005 high-resolution classification and NDVI differencing.

3 Results

3.1 Classification

The use of the generalized 2005 high-resolution Quickbird classification was successful in the mapping of the 1990 Landsat image (Fig. 2). The 1990 classification had an overall accuracy of 86% with a κ statistic of 0.79 (Table 2). All four classes had reasonable error rates. Grasslands and forests were most often confused. Water achieved no error of omission or commission. Impervious surfaces had some confusion with grasslands.

NDVI differencing identified change related to MRD in our study area (Fig. 3). The NDVI differencing method captured patterns of development as seen in the linear patterns and clustering of change pixels around the two major areas of development in Big Sky, the Mountain Village and the Meadow Village. The NDVI differencing method did not result in excessive amount of false-positive change identification. The use of the forest boundary also aided in the minimization of false-positive change identification.

3.2 Spatial Pattern Analysis

Analysis of from-to change indicated that the proportion of from-to changes were disproportionate to the original land cover represented in 1990 (Tables 3 and 4). Forest change accounted

Table 2 Error matrix for 1990 Landsat TM classification. Columns represent reference classes, whereas rows represent how the pixels were classified.

	Grasslands/ shrublands	Impervious surfaces	Water	Forests	User's accuracy
Grasslands/shrublands	81	5	0	12	83%
Impervious surfaces	0	57	0	0	100%
Water	0	0	14	0	100%
Forests	26	1	0	120	82%
Producer's accuracy	76%	90%	100%	91%	

Overall accuracy = 86% $\kappa = 0.79$

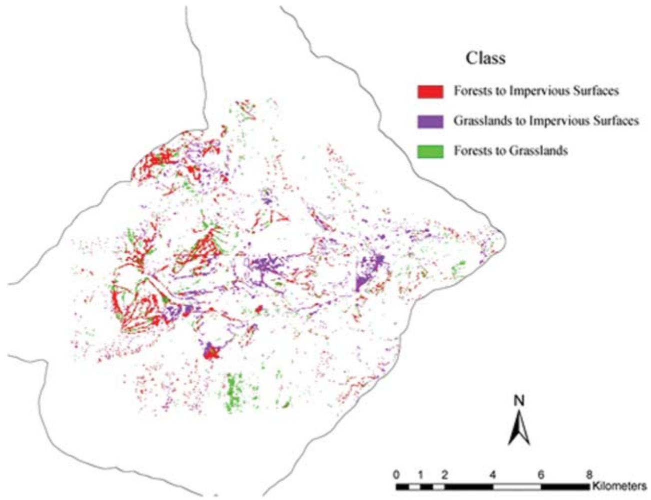

Fig. 3 Classified NDVI difference image showing temporal from-to change classes.

for 67% of the total changes between 1990 and 2005. Forest, however, only accounted for 51% of the land cover in 1990. Grassland changes were proportional to its 1990 land cover.

The three change classes had differences among them for each of the variables. GI had the smallest slope mean followed by FG and FI changes (Table 5). The three change classes differed in the mean response for distance to roads. GI had the shortest distance followed by FI and FG. FI and FG changes had similar mean values for distance to streams.

The proportion of 1990–2005 land-cover changes to the overall proportion of land-cover classes in 1990 for each variable was also examined. Mean and standard deviation for slope and grassland change did not differ from the values for grasslands in the 1990 classification (Table 6), although GI changes occurred on less steep slopes than the mean for grasslands. FI and FG changes were combined in order to investigate overall amount of forest loss. Forest changes occurred on a lower mean slopes than the overall mean forest slopes in the 1990 classification.

Mean changes in forests and grasslands were located closer to roads than the mean response of forest and grasslands in the 1990 classification. Both forest and grassland changes averaged 300 m closer to roads than the mean forest and grassland distance in 1990 classification. The standard deviations of forests and grasslands changes were also smaller than the standard deviation of forest and grassland in the 1990 classification (Table 7).

Changes in forest and grasslands differed from each in their mean response for distance-to-stream (Table 8). Forested change was located farther way from streams than the mean forest distance in the 1990 classification. Grassland change, however, was located closer to streams than the mean grassland distance in the 1990 classification.

The relationship between forest and grassland conversion was also examined with respect to aspect (Table 9). The overall proportion of forest change and the proportion of forest in the 1990

Table 3 Percentage of each change class to the total amount of change between 1990 and 2005.

Change class	Percent of change (%)
FI	48
FG	19
GI	33

Table 4 Land cover percentages in 1990 Landsat classification.

Classified as in 1990	Percent of Land Cover in 1990 (%)
Grasslands	29
Impervious surface	19
Forest	51
Water	1

Table 5 Mean value for variables for from-to change classes.

Change class	Slope (deg)	Distance-to-roads (m)	Distance-to-streams (m)
FI	14.0	177.7	646.0
GI	9.4	90.3	397.3
FG	12.4	337.8	601.0

Table 6 Table of mean and standard deviation values for the variable slope for forest and grasslands.

	Mean slope values for 1990 land-cover class area (deg)	Mean slope values for 1990–2005 land-cover class conversion area (deg)	Standard deviation of slope for 1990 land-cover class area	Standard deviation of slope for 1990–2005 land-cover class conversion area
Forests	16.5	13.0	9.2	8.4
Grasslands	12.5	12.4	8.6	6.8

Table 7 Table of mean and standard deviation values for the indicator variable distance-to-roads for forest and grasslands.

	Mean distance-to-roads values in 1990 classification	Mean distance-to-roads value in change classification	Standard deviation of distance-to-roads in 1990 classification (m)	Standard deviation of distance-to-roads in change classification (m)
Forests	637.7	317.0	724.7	392.4
Grasslands	397.0	90.3	624.9	267.8

Table 8 Table of mean and standard deviation values for the indicator variable distance to stream for forest and grasslands. Distance-to-stream is represented in meters.

	Mean distance-to-stream values in 1990 classification (m)	Mean distance-to-stream value in change classification (m)	Standard deviation of distance to stream in 1990 classification (m)	Standard deviation of distance to stream in change classification (m)
Forests	550.7	649.1	400.9	413.9
Grasslands	516.2	397.4	409.3	321.9

Table 9 Proportion of forest and grassland for nine different aspects to the overall amount of forest and grassland in their classification.

	Percent of forest change between 1990–2005 (%)	Percent of forest class in 1990 classification (%)	Percent of grassland change between 1990–2005 (%)	Percent of grassland class in 1990 classification (%)
North	17	15	19	15
Northeast	20	17	19	17
East	14	15	12	16
Southeast	17	11	14	15
South	10	10	12	13
Southwest	6	10	7	8
West	5	8	4	6
Northwest	11	14	13	8
Flat	0.001	0.001	0.001	0.001

classification to aspect were similar. The largest difference between forest change proportion and forest 1990 classification proportion was in the southeastern direction with 6% less changed than represented in the 1990 classification. Grassland changes in aspect were also similar to the proportion of grassland aspect in the 1990 classification. The largest difference for grasslands was a 5% decrease in grasslands between 1990 and 2005 in the northwest direction.

The CT based on the cross-validation model was able to separate the three types of change (Fig. 4). The CT model accounted for 87% of the variance within this data set. FI change was separated into four different groups. Three of the groups were located less than 63.5 m from roads, while one group was located greater than 63.5 m from roads. GI change was grouped into three groups, two being closer to roads than the last. All three change classes occurred in areas greater than 63.5 m from roads. FG was captured in a single group of change and was located greater than 63.5 m from roads.

The mapped classification tree displays the spatial patterns of from-to changes (Fig. 5). Class A represents a dense cluster of GI change. This particular group of change was caused by development of the area known as Meadow Village. FI change due to the creation of ski slope is seen mostly in classes E and H. Class E, however, also captures the FI change of Mountain Village. The small amount of FG change can be seen in an area with little development and attributed to forest management practices such as logging.

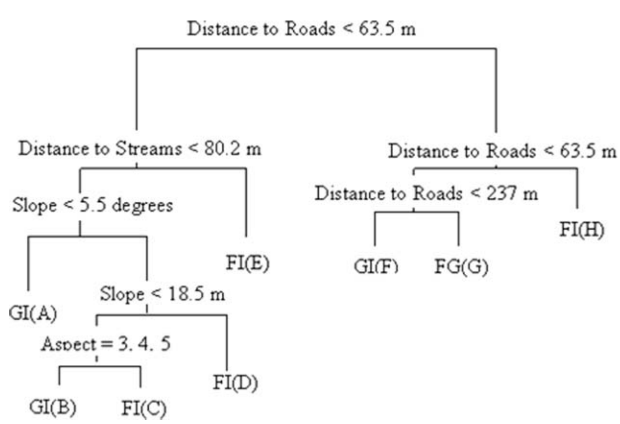

Fig. 4 Classification-tree results. Branch length is proportional to amount of deviance explained. End nodes represent the from-to change class. Nodes were coded alphabetically in order to map their spatial distribution (Fig. 5).

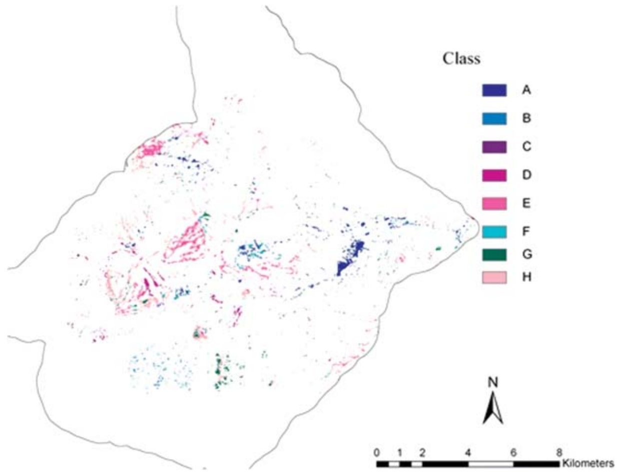

Fig. 5 Classification tree based classified map of from-to changes. Each class is coded alphabetically to match tree nodes from left to right (Fig. 4).

4 Discussion

4.1 Image Classification

The successful use of the 2005 high-resolution Quickbird classification to map historical land-cover patterns in the 1990 Landsat image was largely due to the successful identification of changed areas and the use of boosted CT. NDVI image differencing ability to identify change is a testament to the method's robustness in capturing vegetation loss and tolerance of topographic variables. The speckled mountain slope indicates that some false-positive change could have been identified. These changes could be related to difference in vegetation health, amount, or structure between years, annual variation in snow melt, or residual geometric errors.

NDVI differencing did not capture all differences between dates. The two images used represent snapshots of the land's surface at given moments in time. Forest areas that could have been clear cut prior to 1990 and in the phase of regrowth in 1990 and 2005 were not captured by the NDVI differencing method. This might be a deficiency of the NDVI differencing method for vegetation monitoring purposes. Our study, however, was not about forest management practices or vegetation dynamics. The appropriate method of change identification is related to change one hopes to identify, and NDVI differencing worked well for identifying MRD.

The success in the change identification resulted in the successful classification of the 1990 Landsat image. The classification was largely based on the assumption that areas with minimal change in NDVI were really areas of no change. A current classification with a known accuracy and known land cover could then be used to map the historical image. Taking the classified changed areas and merging them with the current classification reduced the compound error often associated with multiple classifications.[36] Compound error arises in independent classifications because sources of error in the two classifications are largely independent. Compound error can reduce the accuracy of the postclassification comparison methods by multiplying the error rates in each classification and greatly reducing the accuracy of the comparison. Compound error is reduced in the approach used in this study by classifying only once a large portion of the study area that did not change between the two dates.

4.2 Analysis of Temporal Change

Impervious surfaces encapsulated many different types of spectrally similar LULC types in both classifications. Impervious surfaces represented the scree and talus present on the mountain peaks and slopes, while at the same time representing human-induced land cover, such as roads and residential and commercial development. The amalgamated land cover that impervious surfaces represented was of limited utility for the individual classifications, but did provide great insight into our temporal analysis because change from vegetated to impervious surface was likely associated with increased MRD.

The 2005 classification had 1185 ha more classified as impervious surfaces than in the 1990 classification. This cannot be related to absolute increases in impervious surfaces because the 30-m pixel size resulted in an abundance of pixels with mixed classes and pixels were classified as impervious if 20% of the pixel contained impervious surfaces. The increase in impervious surface was mirrored by a 944 ha decrease in forest and a 270 ha decrease in grasslands. Researchers working in the study area throughout the study period are aware of no catastrophic natural events that occurred between the two dates that could have caused such an increase. Forests and grasslands/shrublands conversion to impervious surfaces were therefore likely a result of MRD-induced land-cover changes.

Results from the descriptive statistics indicated the conversion of forests and grasslands to impervious surfaces was not proportional to their respective land cover in 1990. This can be seen in the 67% of change being forest, when forest only accounted for 51% of the land cover in 1990. This significant amount of forest loss can have negative repercussions for ecosystems within the area. Most of the forest loss can be seen as having a linear pattern. This is likely a result of the addition of ski runs to the landscape. These linear patches differ from forest logging patches, such as clear cuts, in that they create multiple smaller patches of forest and that these patches are essentially permanent. This results in increased habitat fragmentation than would have occurred with a clear cut. The effects of habitat fragmentation have been shown to result in decreases in species composition distribution and abundance for both flora and fauna of an area.[2–4]

Previous studies have found topographic variables useful for identifying amenity development.[11] Our topographic variables, aspect, and slope did not provide much information in the proportion of change from 1990 to 2005 to land cover in 1990. They did explain some of the variance in the CT model. Aspect was used in the CT to separate two small groups of FI and FG. Slope was used to separate four different groups of change in the CT.

The variables distance to streams and distance to roads were effective at explaining some of the variance within our change data. Forest and grassland changes, in general, were found closer to roads than the mean land cover in 1990. This, however, was at least in part a result of roads being the actual change identified. MRD also generally includes road development for access. Previous studies have found that the introduction of roads to the landscape often facilitates development.[7] Accurate road data, however, does not exist for 1990. We cannot, therefore, determine if this is true for our case. We can use today's roads to identify possible area of future development.

The distance-to-stream variable provided good information on our types of change. Previous studies have found that proximity of water is a good indicator of amenity development.[11,27] Our data showed that development of grasslands was disproportionately closer to streams than grasslands in general. This could likely be a result of amenity development at or near the water edges.[8,9] The proximity of Meadow Village, a major focus of development, to the West Fork of the Gallatin River certainly accounts for a large portion of this change. Forest change, however, was found farther way from streams than the mean forest land in 1990. These relationships could also be a result of grasslands naturally occurring closer to water on average than forested land, which often occurs on upland mountain slopes.

5 Conclusion

High-resolution imagery was successfully used with moderate-resolution imagery to map changes in land-cover patterns in Big Sky, Montana. Previous research in this area has been lacking. Our research indicated that the generalization of a high-resolution classification can be used as training data for a historical image.

The use of NDVI image differencing and boosted CT resulted in the successful identification of land use change due to MRD. The NDVI differencing method allowed only areas of change to be identified and reclassified. This decreased the compound error associated with postclassification comparisons. Boosted CT handled both the training data and the spectral data well. This is largely a result of the robustness of the classifier. Future research should be in the form of mapping more than two dates. This can allow for more information on the rate and nature of changes among years.

Statistical pattern analysis demonstrated that our indicators could be used to explain the change within our study area. We found forests to have a disproportionate amount of change when compared to their overall amount of land cover. We also found that forest changes were located farther away from streams and tended to occur on lower slopes than their overall amount of land cover. Grassland change occurred closer to steams than its land cover in 1990, and its change was proportional to its land cover. These variables explained 87% of the variance for the change classes and might be related to amenity development.

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