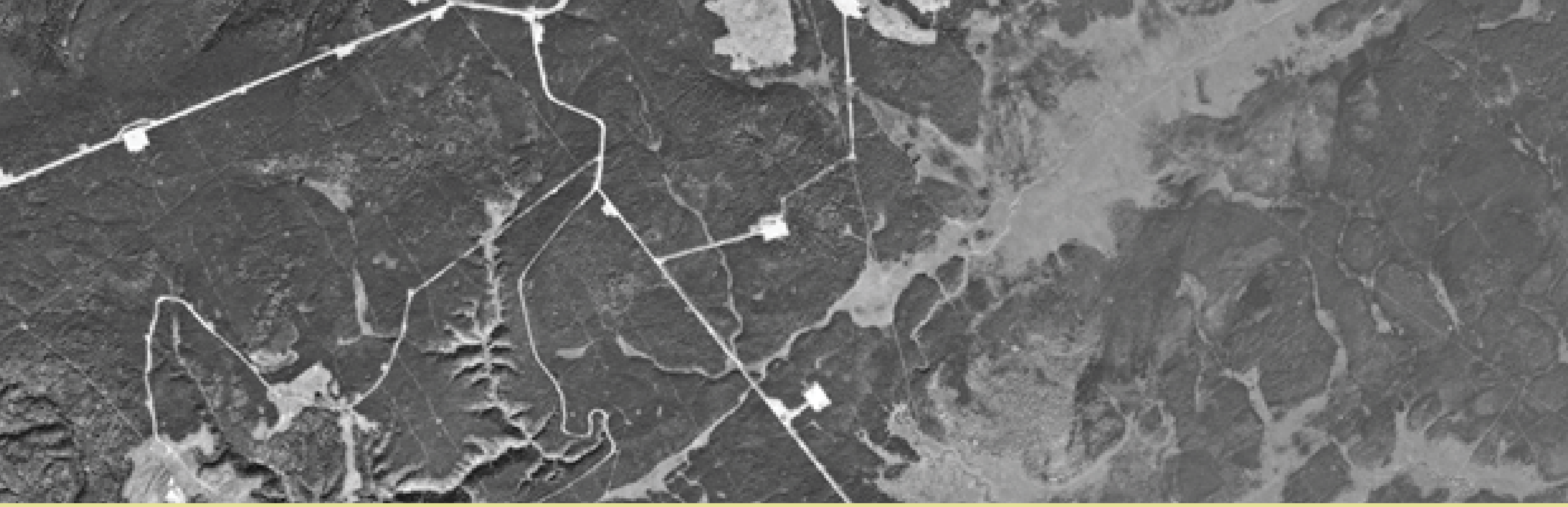

IMAGE AGE CLASSIFICATION SYSTEM FOR ANTHROPOGENIC FEATURES

Project Status Report

May 2015

Prepared by:

CASLYS CONSULTING

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Executive Summary

The objective of the project was to conduct a pilot to assess the cost, practicality and accuracy of using SPOT imagery to attribute existing features with an age (or activity level) class. In addition, the classification method was to facilitate the addition of any unmapped linear features (i.e., recent disturbances) absent from the current datasets. The resultant data layers facilitate the generation of density maps depicting the level of human disturbance within a given area. These density maps would then be used to examine the potential effects of human disturbance on the habitat of various species including the boreal caribou.

A method was developed to classify the imagery to identify disturbance features present within the imagery. This classification effectively modelled the amount of disturbance activity, allowing a use level to be assigned to each feature. To calibrate the results the data for roads, trails and polygonal features were edited to incorporate any missing features and resolve any spatial differences between the vector features and their location in the imagery. The amount of each feature captured by the classification model was then quantified and summarized. The results of this summary were then examined to determine if class breaks were present in the data that would facilitate the assignment of an activity level to the features to indicate whether the feature was being used frequently, infrequently or was not being utilized (i.e., the feature was overgrown). The preliminary results indicated that a use classification could successfully be assigned to the features. The project resulted in the following key findings and recommendations:

- The model facilitates a semi-automated approach to the capture of new disturbance features. In some areas the model could be used to derive mapped features directly (i.e., through conversion of the raster data to vectors). However, in areas with only a few missing features it would be more practical to manually update the vector dataset by heads-up digitizing the missing features.
- The model makes it much easier (and therefore cost effective) to update human disturbance data because missing features are much easier to identify.
- The results of the pilot project indicate that use levels can be assigned to features to help quantify the amount of active human disturbance present in the landscape.
- The model is extremely effective at identifying the active footprint associated with disturbance features.
- The results should be verified in the field. Ideally, photos should be taken with an associated GPS coordinate and accompanying descriptive text indicating the direction of the photo. These photos could then be linked to specific locations to facilitate a more detailed evaluation of the model and subsequent refinement of the results.
- The model results could be used to identify and map wildlife movement corridors for different species. In effect the model allows 'low cost' movement pathways to be identified. These pathways could be used to evaluate prey/predator relationships which is of particular relevance to boreal caribou in this area.
- The model allows the accessibility of given areas to be better quantified through the identification of active trails, rough roads and seismic lines that facilitate human access.
- The results of the model could potentially be used to monitor the success of reclamation efforts because areas of vegetation regrowth can be quantified easily.
- It would be worthwhile to conduct a pilot project to examine how the model could be used to more effectively identify linked pathways in the data (i.e., improve the connections between linear features to yield a seamless, connected transportation/disturbance network).
- Scenarios for different time periods could be developed through the acquisition and classification of imagery for given years. This would result in a multi-temporal dataset that would be of relevance in cumulative effects assessment.

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1.0 INTRODUCTION

Data concerning the locations of human disturbance on the landscape may be found in a variety of different sources: Oil and Gas Commission (OGC) datasets, the Terrain Resource Information Management (TRIM) dataset and the province's Integrated Transportation Network. However, due to the level of effort associated with maintaining the data, much of the information is not current. Numerous features (e.g., seismic lines, wellpads, pipeline right-of-ways, and resource roads), not in active use, have become overgrown and therefore do not have the same environmental impact as more recent disturbances. There is a need to develop a cost-effective approach to updating the status of these features to improve the temporal accuracy of the data.

The objective of the project is to conduct a pilot to assess the cost, practicality and accuracy of using SPOT imagery to attribute existing features with an age (or activity level) class. In addition, the classification method should facilitate the addition of any unmapped linear features (i.e., recent disturbances) absent from the current datasets. The resultant data layers will facilitate the generation of density maps depicting the level of human disturbance within a given area. These density maps would then be used to examine the potential effects of human disturbance on the habitat of various species including the boreal caribou.

There are a number of potential technical challenges associated with extraction of disturbance features from imagery, particularly in forested areas. These include having to address shadows in the imagery, tree canopy covering portions of linear features, overgrown roads, and roads running through other types of human disturbance (e.g., timber harvest areas and well pads). The proposed study area for this pilot project provided an ideal test location because these conditions are all present throughout the study area. This report details the methods used and presents the results of the project.

2.0 METHODS

The following sections detail the methods used to classify the imagery and identify disturbance features. The work was conducted using PCI Geomatica for classifying the imagery with ESRI's ArcMap Version 10.x being used to capture and attribute the disturbance features.

2.1 Source Data Layers

The following datasets, each clipped to a polygon defining the extent of the study area, represent the source data layers used in the analysis:

2.1.1 Digital Imagery

SPOT imagery at a resolution of 2.5 metres was provided by the Oil and Gas Commission (OGC) for use on the project

Purpose:	Base layer reflecting current disturbances in the study area
Source:	OGC
Date:	2011
Scale:	2.5 metre cell size

Three SPOT scenes were selected to represent the study area for the pilot project (Figure 1). The scenes were selected because they provided a representative sample of varying levels of human disturbance and boreal caribou density. In addition, Scene E overlapped an area with available LiDAR data.

2.1.2 Freshwater Atlas Streams

The Freshwater Atlas is a standardized dataset for mapping the province's hydrological features. It is derived from the province's 1:20,000 scale topographic base maps (TRIM). The atlas defines watershed boundaries by height of land and provides a connected network of streams, lakes and wetlands.

Purpose:	Used as a reference dataset to ensure streams were not erroneously captured as linear features.
Source:	B.C. Land and Resource Data Warehouse
Date:	assorted
Scale:	1:20,000

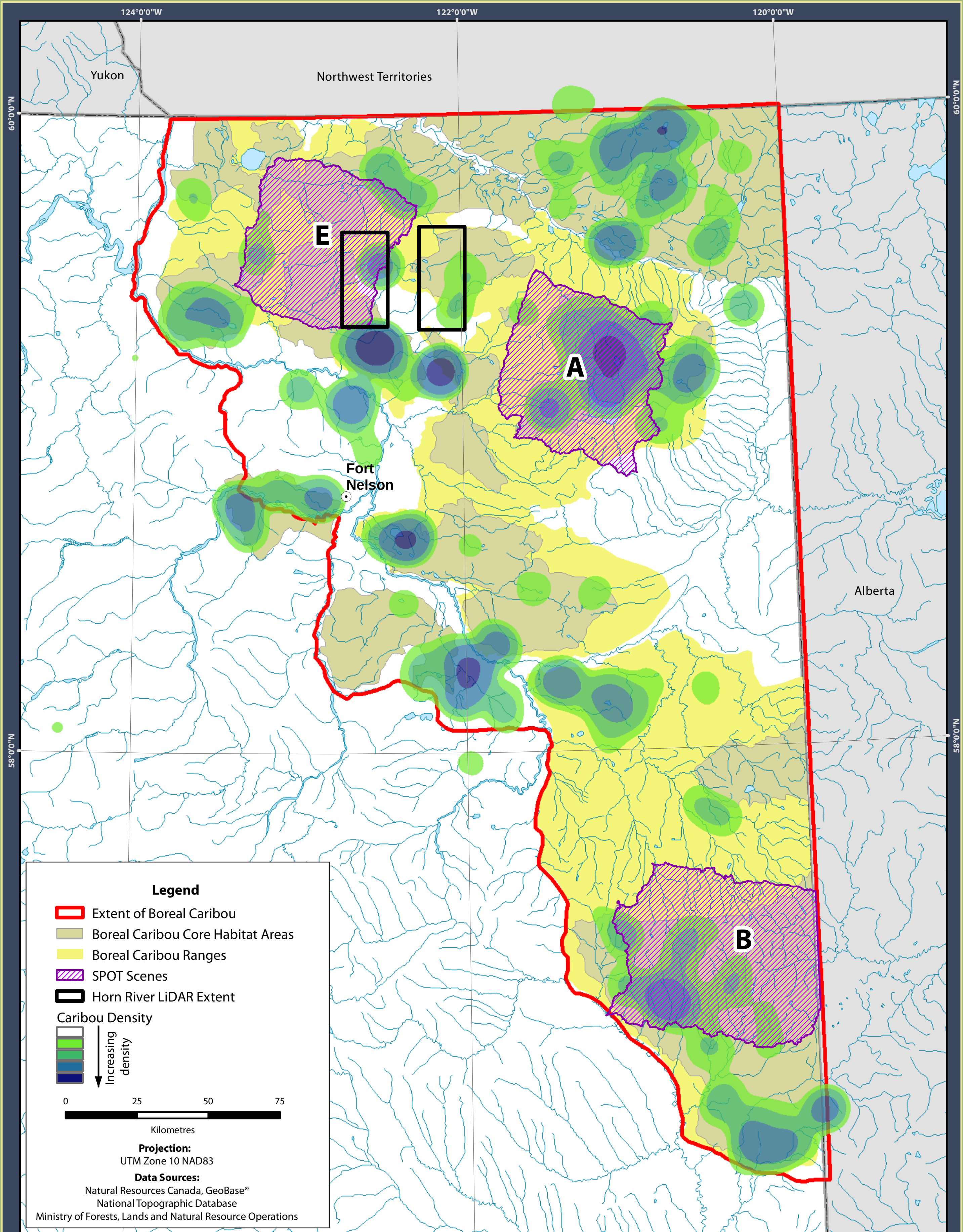
2.1.3 Consolidated GeoBC Atlas Integrated Transportation Network

The consolidated GeoBC Atlas Integrated Transportation Network builds on data from the Digital Road Atlas integrating GDM transport lines and as-built forestry roads.

Purpose:	The dataset served as the starting point in the identification of new roads.
Source:	GeoBC Atlas
Date:	The dataset represents a compilation of transportation features mapped from the 1980s onward.
Scale:	1:20,000

Figure 1: Study Area SPOT Scenes with Caribou Density

DRAFT



2.1.4 Well Pads

Well pads were provided by the OGC.

Purpose:	Used to identify and date well pad features
Source:	OGC
Date:	The dataset represents well pad clearings mapped from October 2006 onward.
Scale:	assorted

2.1.5 Pipelines

Pipelines were provided by the OGC.

Purpose:	Used to identify and date pipeline features
Source:	OGC
Date:	Data collection began in October, 2004, but includes pipeline applications from February, 2000.
Scale:	assorted

2.1.6 Seismic Lines

Seismic lines were provided by the OGC.

Purpose:	Used to identify and date seismic line features
Source:	OGC
Date:	The dataset represents a compilation of seismic lines mapped from 1996 to 2004, 2002 to 2006, and October 2006 to present.
Scale:	assorted

2.2 Image Enhancement

Each of the source images (Figure 2) was enhanced with a linear contrast stretch to more clearly define the disturbance features. The result of this process increases the accuracy of the detection process. The illustrated enhancement (Figure 3) allows smaller features (e.g., narrow roads) to be more readily identified - the enhancement makes the roads in the upper left part of the image more distinct.

Figure 2. Raw SPOT Source Imagery

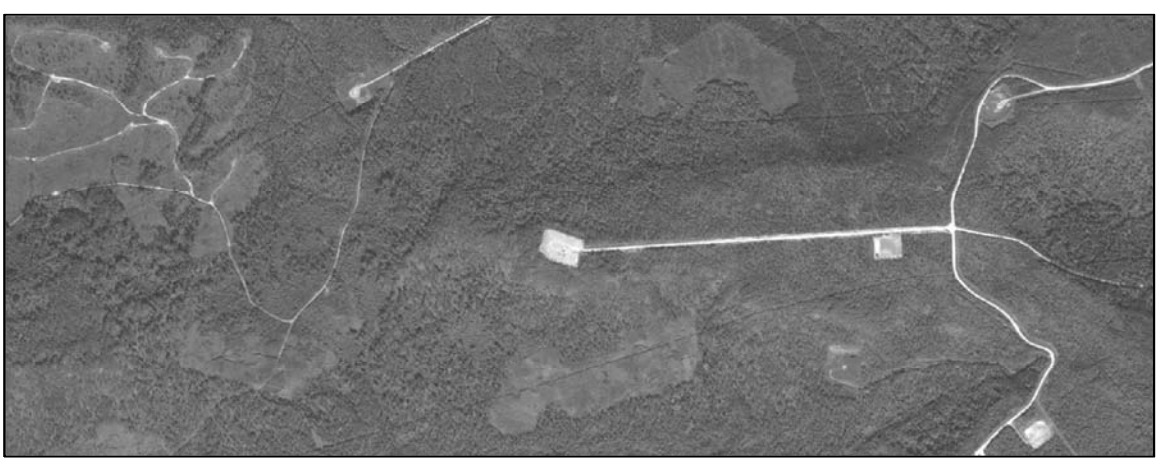
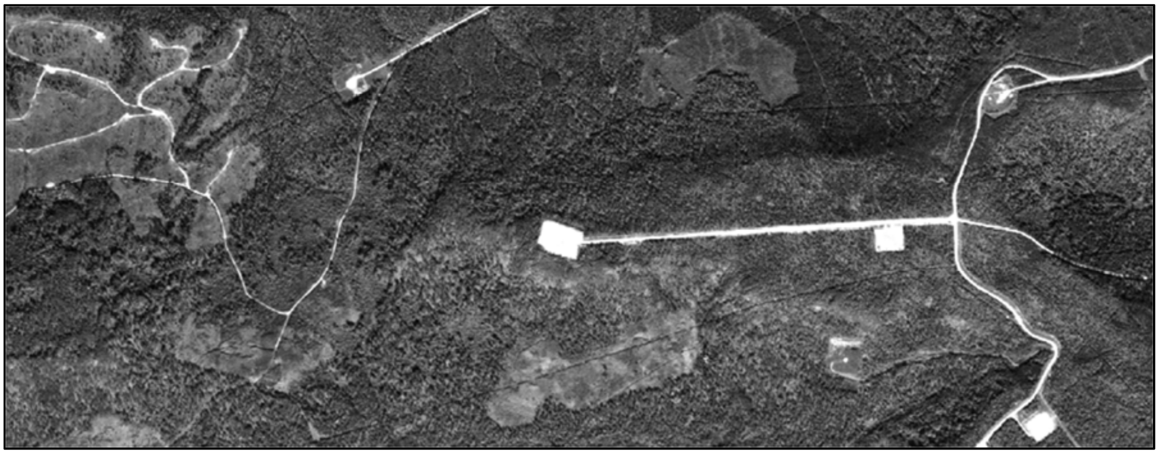


Figure 3. Enhanced SPOT Image Example



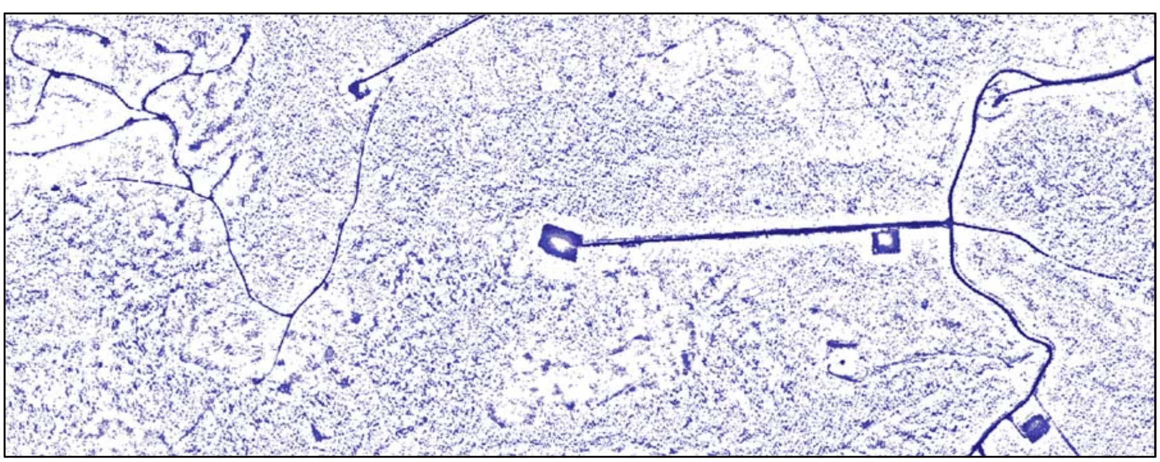
2.3 Image Classification

Subsequent to the enhancement, an unsupervised classification was conducted in PCI. Typically, this type of classification is performed when there is no prior knowledge of the classes in a scene. The spectral signatures of individual pixels are compared to the signatures of computer-derived classes and then each pixel is assigned to one of these classes. The classification yielded 16 to 25 unique classes within each image.

2.4 Topographic Position Index

A Topographic Position Index (TPI) was applied to the identify disturbance features (Figure 4). The application of this approach is particularly helpful in closing gaps that may exist due to the presence of tree and tree shadow across portions of a feature. While TPI is designed to be applied to a DEM to identify areas as top-of-slope, bottom-of-slope or mid-slope, when applied to a SPOT image, the algorithm enhances linear features, closes some gaps to create more continuous linear features and most importantly, removes a substantial amount of image texture noise adjacent to the features. In effect, 'noise free' corridors surrounding the features are created, resulting in an image surface that greatly improves the delineation of disturbances.

Figure 4. Topographic Position Index Output Example



2.5 Disturbance Model

The results of the unsupervised classification and the TPI analysis were then integrated to yield a model that identified disturbance features within each image. The results of the TPI analysis were multiplied with the classification results to produce a derivative raster dataset which was then classified into ¼ standard deviation breaks and the largest (highest values) 5-8 classes were extracted and used as the model result. The results of the model made it very easy to identify disturbance features in a variety of landscapes.

2.6 Adding New Features

The results of the model clearly identified disturbance features (Figure 4), however the majority of the features were only partially captured by the model (i.e., they were represented by a discontinuous set of pixels). The utility of the model is that it allows the operator to more readily identify missing disturbance features because a dashed line is as easy to see as a solid line.

To aid in the process, existing linear features were assigned a thick line style and layered over the model results, various polygonal datasets were also displayed for reference purposes. These included well pads, seismic lines, rail lines, streams and timber harvest cut blocks. With these data all layered over the results of the model with the SPOT image as a backdrop, features missing from the existing disturbance datasets were easily identifiable.

2.7 Assigning Age Classes to Features

The results of the model were also used to identify those features not currently in use (i.e., overgrown roads and well pads). This was achieved by quantifying the amount of each feature mapped by the model. The premise was that active disturbance features would produce a higher signal and therefore a greater proportion of the feature would be identified by the model. Less active and inactive features would only be partially captured by the model.

To determine if this approach would allow the status of disturbances to be identified, the disturbances for scenes A and E (Figure 1) were reviewed in detail:

- In some instances, the spatial accuracy of the mapped location of existing vectors versus their location on the SPOT image varied by up to five metres. To account for this, the model results were expanded by 2.5 metres.
- To ensure the results were accurate, the any missing features (typically new active disturbances) were digitized and any features with significant spatial errors were repositioned to the correct location as it appeared in the SPOT imagery.
- Overgrown/apparently inactive features were then flagged in the dataset toward the goal of identifying a threshold that could be applied to the 'model percent attribute' that could be applied to automatically identify overgrown features.

From our preliminary results, it appears that if less than 30% of the feature is captured by the model it can be flagged as potentially overgrown. Ideally, these features would also be visually inspected however, the model results allow these features to be identified easily thereby significantly reducing the level of effort associated with generating accurate disturbance datasets. Figures 5 through 7 depict preliminary results indicating how a use status can be assigned to polygonal, road and trail, and seismic line features.

Figure 5. Assigning Use Status Attribute to Polygonal Features

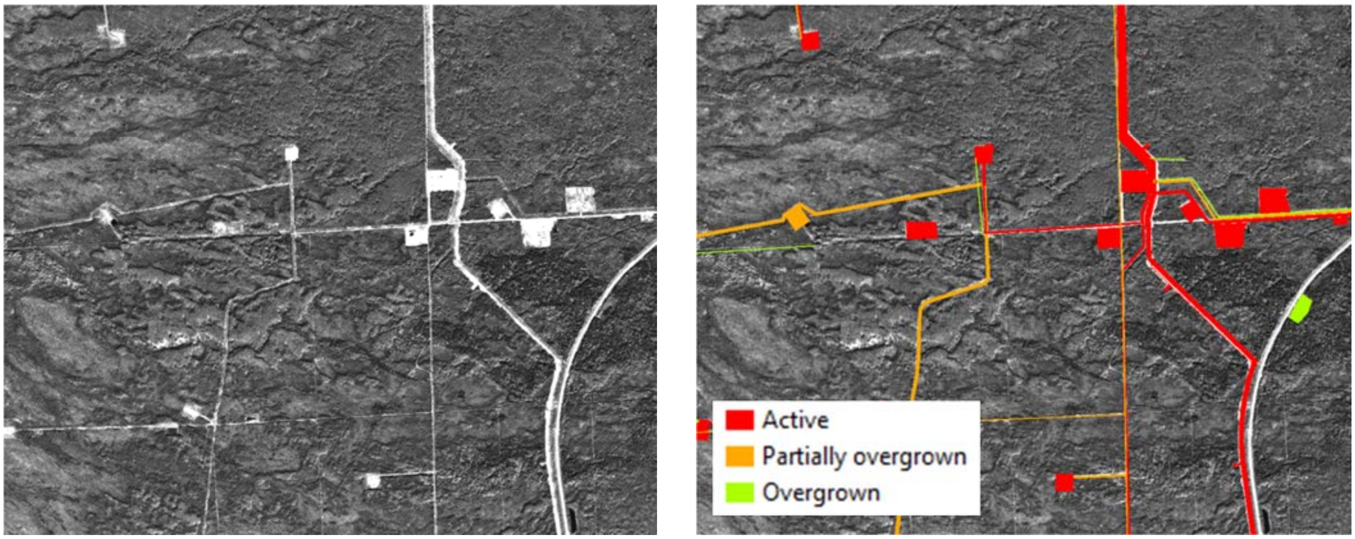


Figure 6. Assigning Use Status Attribute to Roads and Trails

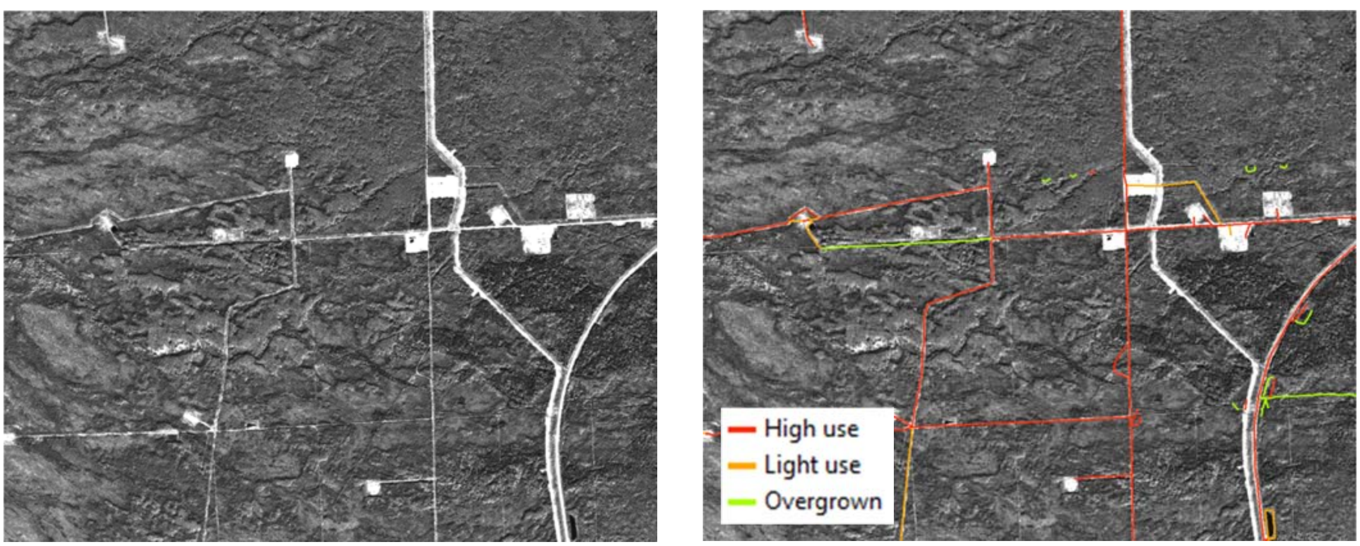
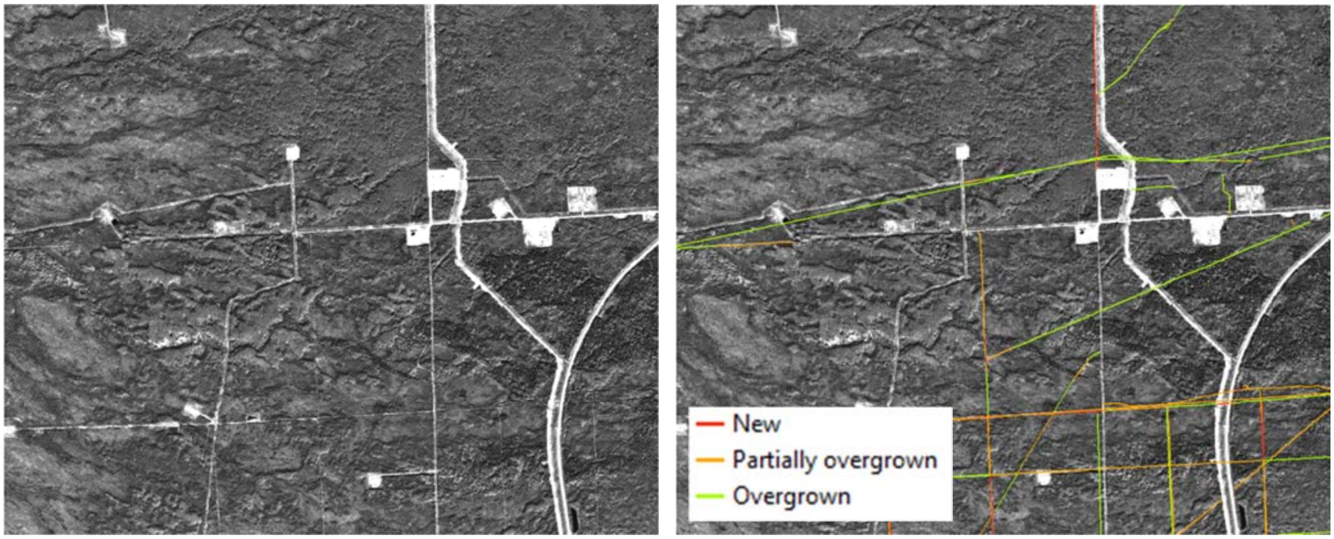


Figure 7. Assigning Use Status Attribute to Seismic Lines



3.0 RESULTS

To more effectively examine the outcomes of the project, the results have been summarized by feature type in the sections below.

3.1 Roads

3.1.1 Data Modifications

A number of factors influence the capability of the model to map road features:

- Image date - Classification of the most recent data available will result in the most accurate current picture of road features on the landscape.
- Tree canopy - Areas where the tree canopy overhangs the road will impact the results of the model: the model will not return a strong signal when the visibility of the feature is blocked by overhanging trees.
- Low use roads – Gravel and rough surface roads that are used infrequently will return a lower signal if they are utilized less frequently. Low utilization allows vegetation regrowth which reduces the reflective characteristics, and the resultant model score, of the feature.
- Spatial differences between datasets – In some cases an existing dataset will map the road, or part of the feature, in a different spatial location (i.e., the road might be shifted a few metres from where it exists in the image). When existing vectors are not aligned with their location in the imagery it is impossible to accurately quantify the model results.
- Temporal accuracy of existing datasets – If existing vectors datasets have been updated recently (i.e., within a few months of the image acquisition date) the number of missing features will be relatively low. Typically, updates are not conducted for all features simultaneously (i.e., roads are updated but not pipeline right-of-ways). This type of temporal variation is relevant in this study area because GeoBC recently (based on 2010-2013 imagery) mapped roads as part of their ongoing resource roads mapping initiative. As a result, fewer roads features were missing from the existing digital datasets than would be expected in other areas of the province.
- The amount of recent road construction – The requirement to update any disturbance dataset will be a function of the amount of recent human activity in the area of interest.

Toward the goal of determining the level of effort required to update existing features, existing roads datasets were amalgamated and compared against the SPOT imagery. In scenes A and E (Figure 1) the vector data were updated: missing features were added and features were repositioned as required to ensure they aligned with the location in the imagery. In addition, an attribute was assigned to each feature to track the number of changes required to update the dataset. The following actions were identified:

- No change – The feature was already present in existing datasets in the correct spatial location.
- New – The feature was not present in existing datasets and was therefore added.
- Missing overgrown – These were features that appeared to be overgrown that were not present in existing digital datasets that were identifiable in the imagery.
- Delete – These were features present in the existing digital datasets that could not be seen in the imagery (i.e., they appeared not to have been constructed).
- Overgrown – Features that appear to have become overgrown based on a review of the imagery.
- Location modified – The feature was present in an existing dataset but the location of all, or part of, the feature required realignment to make it match the location in the imagery.

- Modified overgrown – Overgrown features (as identified by the surface type attribute in the source datasets) that required alignment to the imagery were tracked separately. In theory overgrown features would not have to be mapped to accurately reflect current human disturbance however, for cumulative effects assessment these features would potentially have significance.
- Cutline? – These were features classified as roads in the existing datasets that appeared to be seismic survey cutlines rather than roads.
- Low score – These were features, clearly present in the imagery, that received a relatively low score from the model. Areas where the tree canopy overhangs the road are an example of how features fell into this category.

Table 1 summarizes the number of modifications made to the existing digital datasets to update the roads features for each of the two SPOT scenes. Table 2 and Figure 8 detail the percentage of features by modification type[1].

Table 1. Number of Road Features Assigned to each Action Class

Scene	None	New	Missing Overgrown	Delete	Overgrown	Location Modified	Modified Overgrown	Cutline?	Low Score	Grand Total
Scene A	4,573	27	20	34	334	32	14	1	14	5,049
Scene E	1,405	16	15	64	177	64	22	12	10	1,785
Grand Total	**5,978**	**43**	**35**	**98**	**511**	**96**	**36**	**13**	**24**	**6,834**

Table 2. Percent of Road Features Assigned to each Action Class

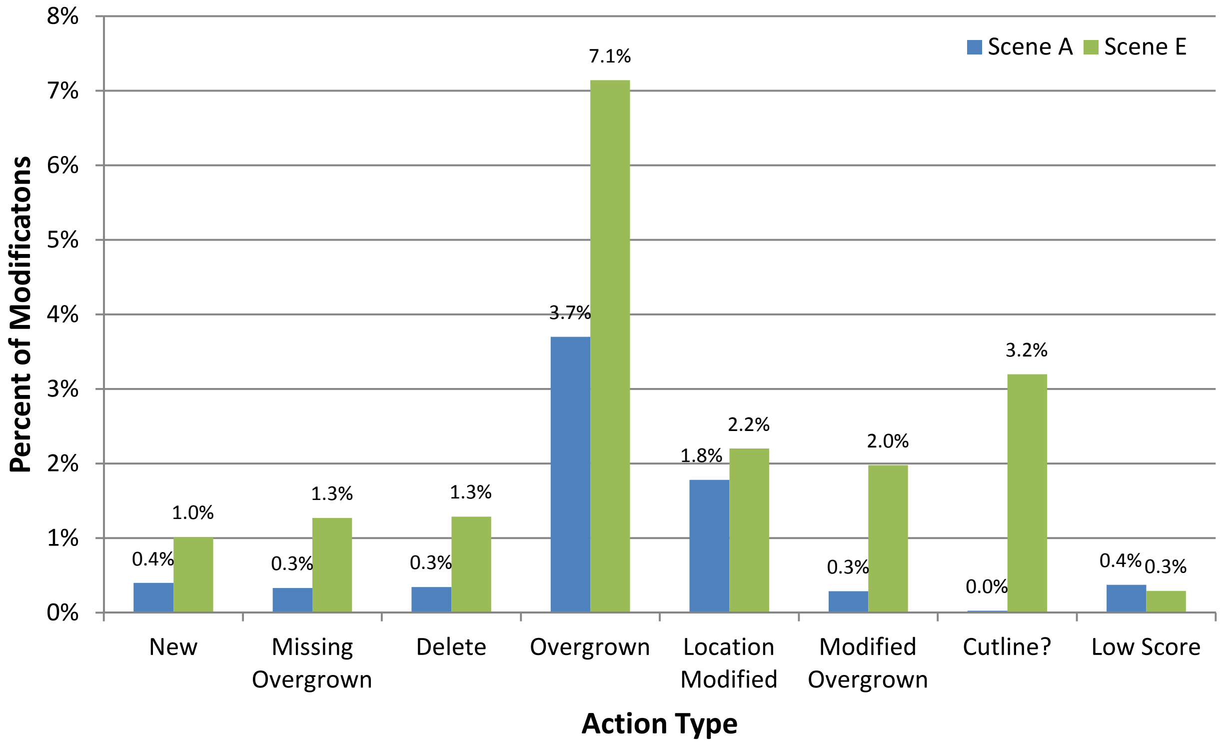
Scene	None	New	Missing Overgrown	Delete	Overgrown	Location Modified	Modified Overgrown	Cutline?	Low Score
Scene A	92.7%	0.4%	0.3%	0.3%	3.7%	1.8%	0.3%	0.0%	0.4%
Scene E	81.6%	1.0%	1.3%	1.3%	7.1%	2.2%	2.0%	3.2%	0.3%

Even though the roads data were updated relatively recently, 7.3% of the features in Scene A and 18.4% in Scene E required some form of modification. The most significant changes as they relate to the development of an up-to-date roads baseline for the two scenes concerned:

- The addition of new features: 27 or 0.4% of the roads features in Scene A were not present in the existing digital dataset and 16 or 1.0% were missing in Scene E.
- 1.8% (32) and 2.2% (64) of the road features in scenes A and E respectively had to be repositioned to ensure there location was in the correct place.
- The most significant modification was the identification of overgrown roads: 3.7% (334) in Scene A and 7.1% (177) in Scene E of the mapped roads appear to have become overgrown.

[1] It should be noted that the percentage change numbers should be interpreted in the context of the number of features in a given scene. If there are a low number of features even a small number of modifications may result in high percent change values.

Figure 8. Percent of Modifications to Road Features by Action Type



3.1.2 Use Summary

Subsequent to the modifications made to the existing roads datasets for scenes A and E, the score for each road was summarized by surface type to quantify the percentage of the road captured by the model. Using the model scores associated with each of the surfaces types, in conjunction with a visual inspection of the imagery, the roads were assigned to one of three classes indicating the amount of use (and therefore potential disturbance present): high use, light use and overgrown. If less than 30% of the road feature was captured by the model it was assigned to the overgrown class, features having 30-75% of the vector being captured by the model were assigned to the light use class and high use class reflects those features where in excess of 75% of the feature was captured. The use classes were then summarized for each of the road surface types for each of the SPOT scenes (Table 3 and figures 9 through 11).

The results indicate that the majority of paved roads 88.9% in Scene A and 100.0% in Scene B fell into the high use class (note that no paved roads were present in Scene E). Relatively few (1.6% to 3.3%) of the roads with a loose road surface (i.e., well maintained gravel roads) were overgrown and the majority of these roads 75.2% to 79.0% fall within the high use class. As would be expected, the results for the rough and overgrown roads were less certain: in Scene A 100.0% of the overgrown roads fell in the overgrown use class however, this statistic decreased to 45.6% in Scene B and 44% in Scene E. The results indicate that potentially ten (10.1 % in Scene E) to twenty (18.7% in Scene A) percent of roads with a rough road surface type are potentially overgrown. Ideally, these results would be verified in the field.

Table 3. Percent of Road Surface Types by Use Class

Road Surface	High use	Light use	Overgrown
Scene A			
paved	88.9%	11.1%	
loose	75.2%	23.1%	1.6%
rough	25.3%	56.0%	18.7%
overgrown	0.0%	0.0%	100.0%
Total Scene A	**61.7%**	**32.2%**	**6.1%**
Scene B			
paved	100.0%		
loose	77.3%	19.3%	3.3%
rough	44.2%	37.5%	18.3%
overgrown	12.4%	42.1%	45.6%
Total Scene B	**64.8%**	**25.9%**	**9.3%**
Scene E			
loose	79.0%	18.7%	2.3%
rough	40.2%	49.7%	10.1%
overgrown	11.6%	44.4%	44.0%
Total Scene E	**72.7%**	**23.7%**	**3.6%**

Figure 9. Percent of Road Use Class by Road Surface – Scene A

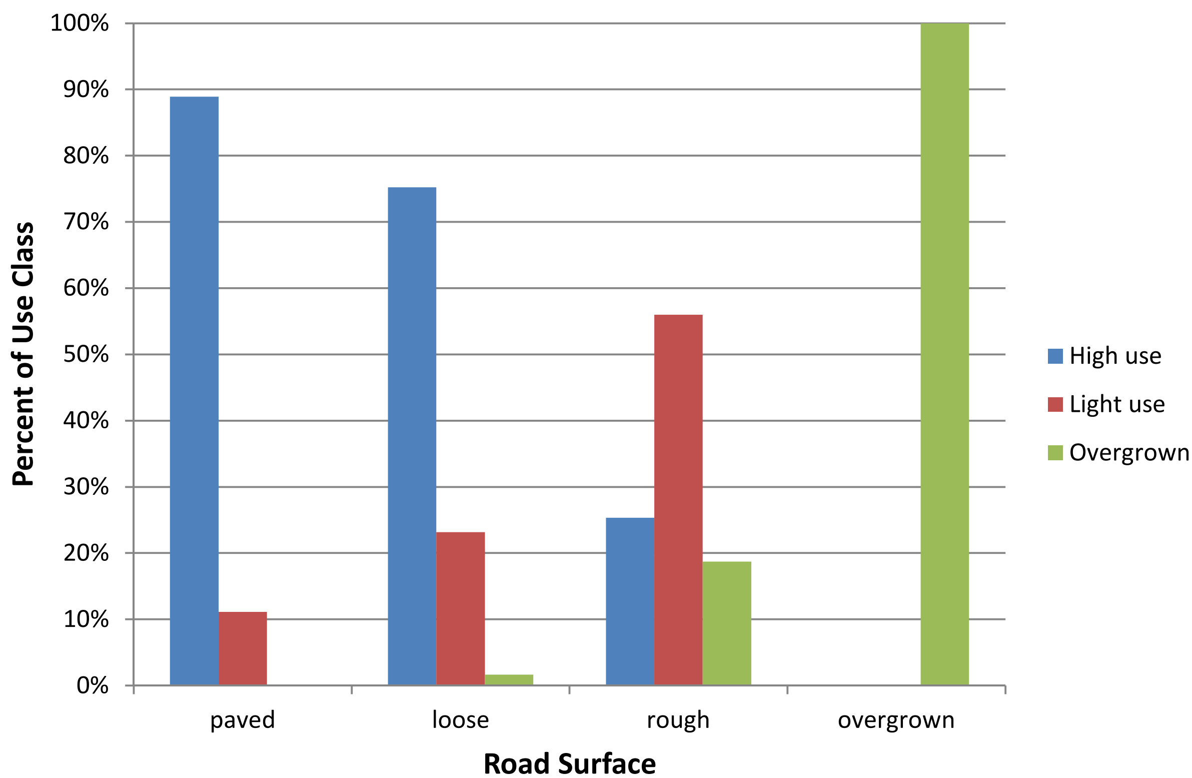


Figure 10. Percent of Road Use Class by Road Surface – Scene B

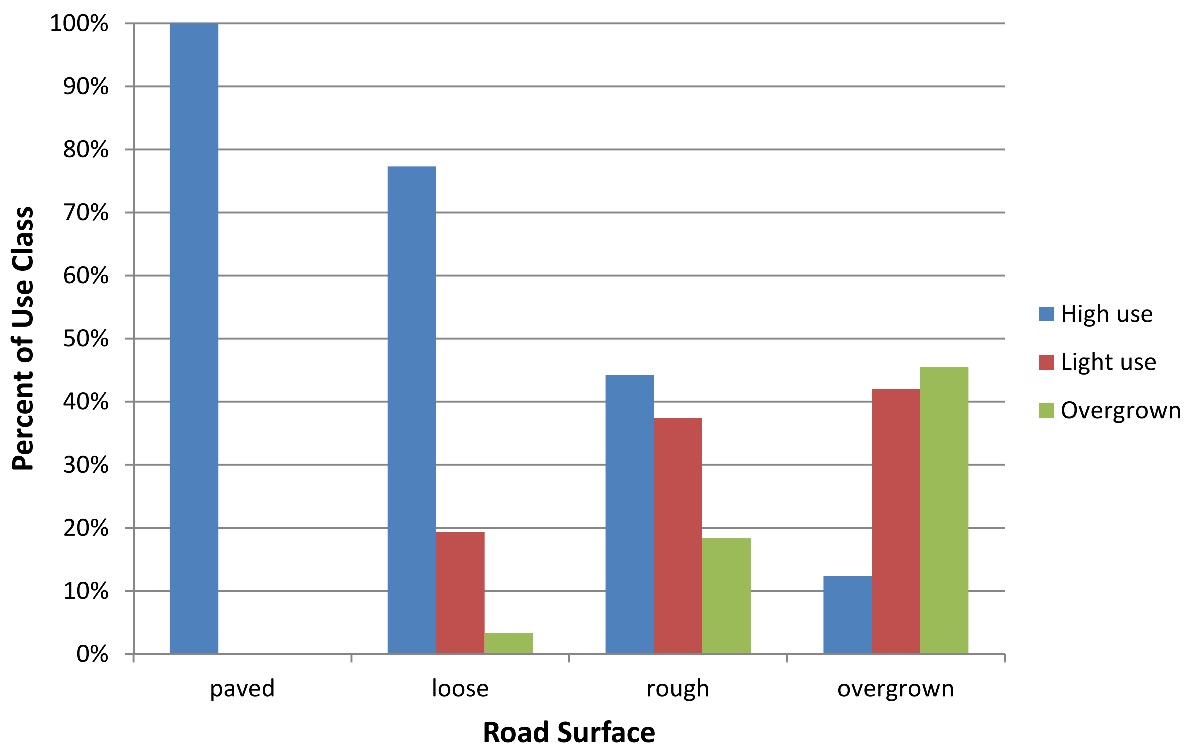
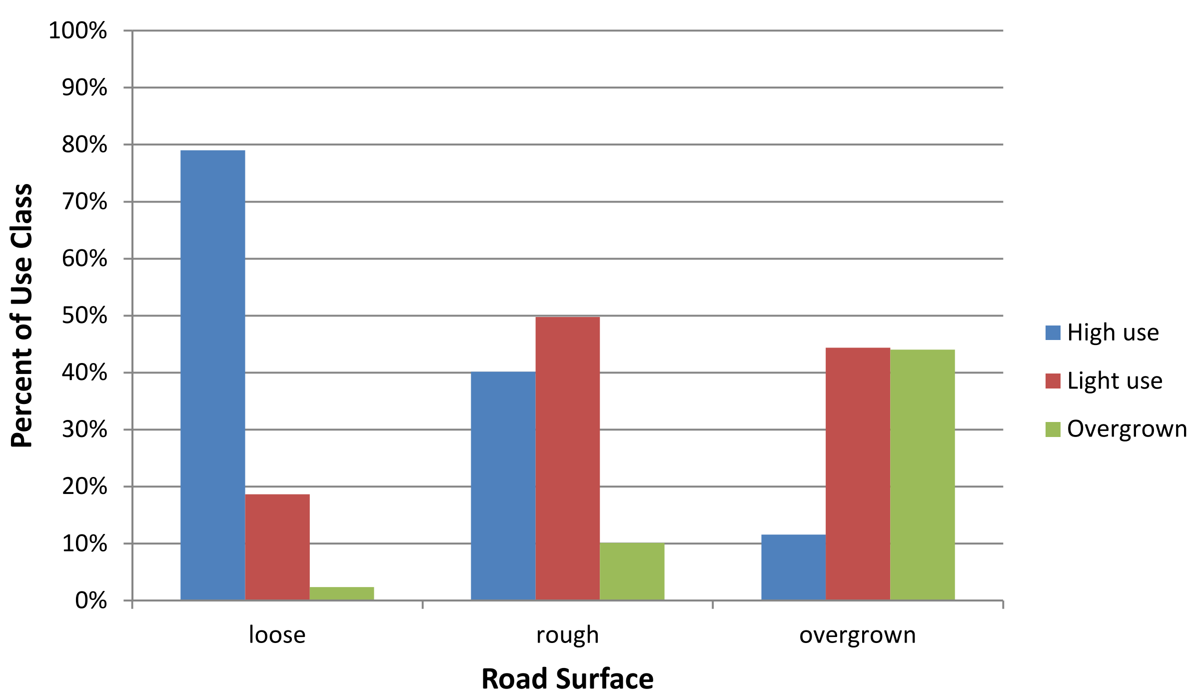
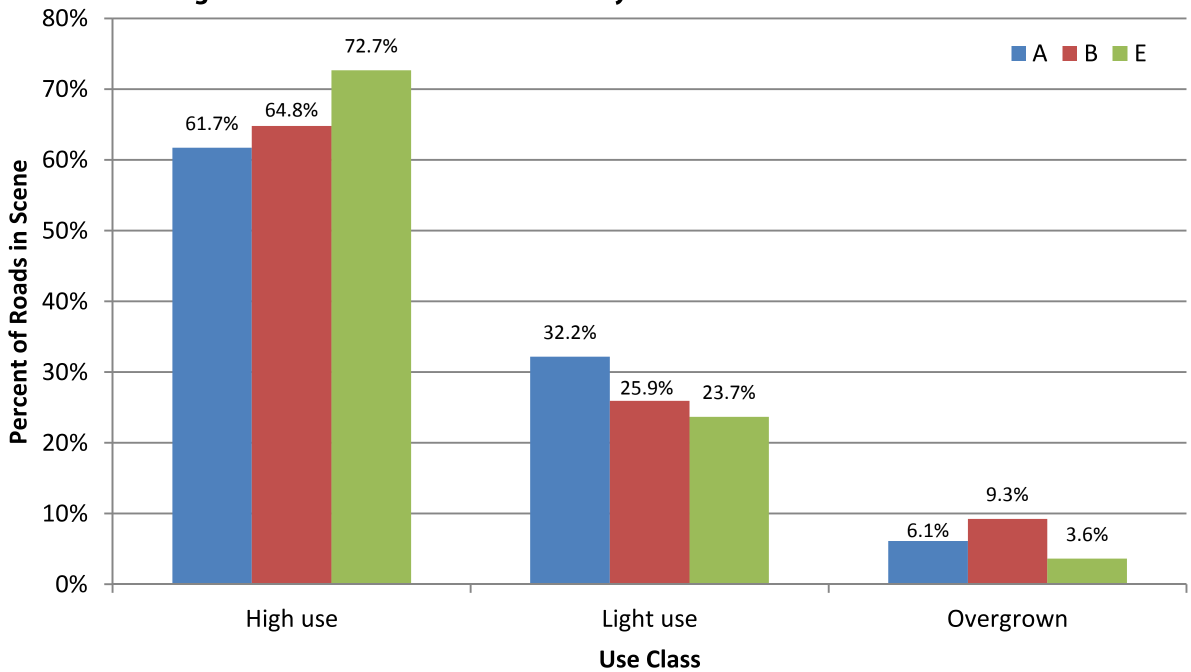


Figure 11. Percent of Road Use Class by Road Surface – Scene E



In summary, as illustrated in Figure 12, between 61.7% to 72.7% of the road features in the three scenes fall into the high use class, roughly a quarter to a third of the roads (23.7% to 32.2%) fall into the light use class and between 3.6% to 9.3% of the roads appear to be overgrown.

Figure 12. Percent of Road Features by Use Class within each SPOT Scene



3.2 Trails

3.2.1 Data Modifications

As with roads, the accuracy of the model in relation to the identification of trails is dependent on the date of the imagery, tree canopy, amount of use the trail is subject to, spatial differences between the location of mapped feature and its location in the imagery, the temporal accuracy of existing datasets, and the amount of recent human activity in the area of interest.

Using the same approach applied to the roads features, the trail features were amalgamated and compared against the SPOT imagery to add missing features, reposition spatially inaccurate linework and identify potentially overgrown features based on an inspection of the SPOT imagery. Table 4 summarizes the number of modifications made to the existing digital datasets to update the trails features for scenes A and E. Table 5 and Figure 13 detail the percentage of features by modification type.

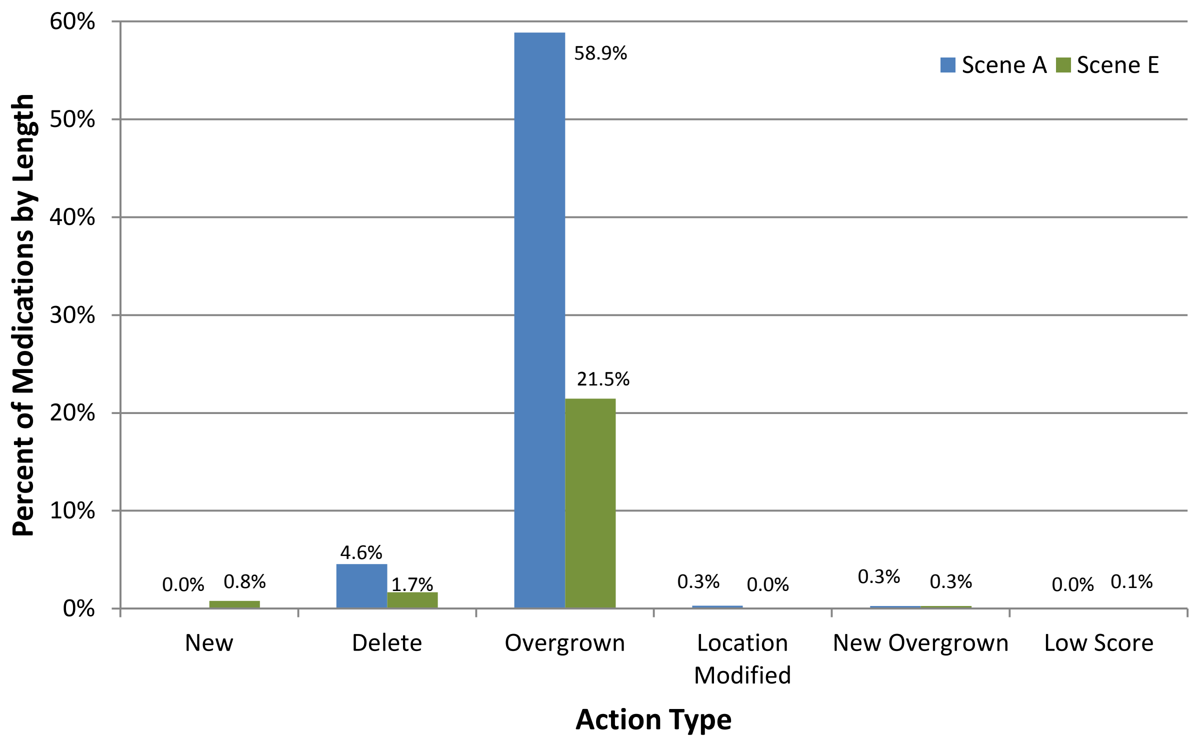
Table 4. Number of Trail Features Assigned to each Action Class

Scene	None	New	Missing Overgrown	Delete	Overgrown	Location Modified	Low Score	Grand Total
Scene A	357	0	3	42	517	6	0	925
Scene E	2,355	9	5	48	601	0	3	3,021
Grand Total	**2,712**	**9**	**8**	**90**	**1,118**	**6**	**3**	**3,946**

Table 5. Percent of Trail Features Assigned to each Action Class

Scene	None	New	Missing Overgrown	Delete	Overgrown	Location Modified	Low Score
Scene A	36.0%	0.0%	0.3%	4.6%	58.9%	0.3%	0.0%
Scene E	75.7%	0.8%	0.3%	1.7%	21.5%	0.0%	0.1%

Figure 13. Percent of Modifications to Trail Features by Action Type



The results related to trails vary significantly between the two scenes: only 36.0% of the features in Scene A required no modification compared to 75.7% for Scene E. The most significant changes as they relate to the development of an up-to-date trails dataset for the two scenes concerned:

- The deletion of 4.6% of trails that did not appear in the imagery in Scene A and 1.7% in Scene E.
- The most significant modification was the identification of overgrown trails: 58.9% (517) in Scene A and 21.5% (601) in Scene E of the mapped trails appear to have become overgrown.

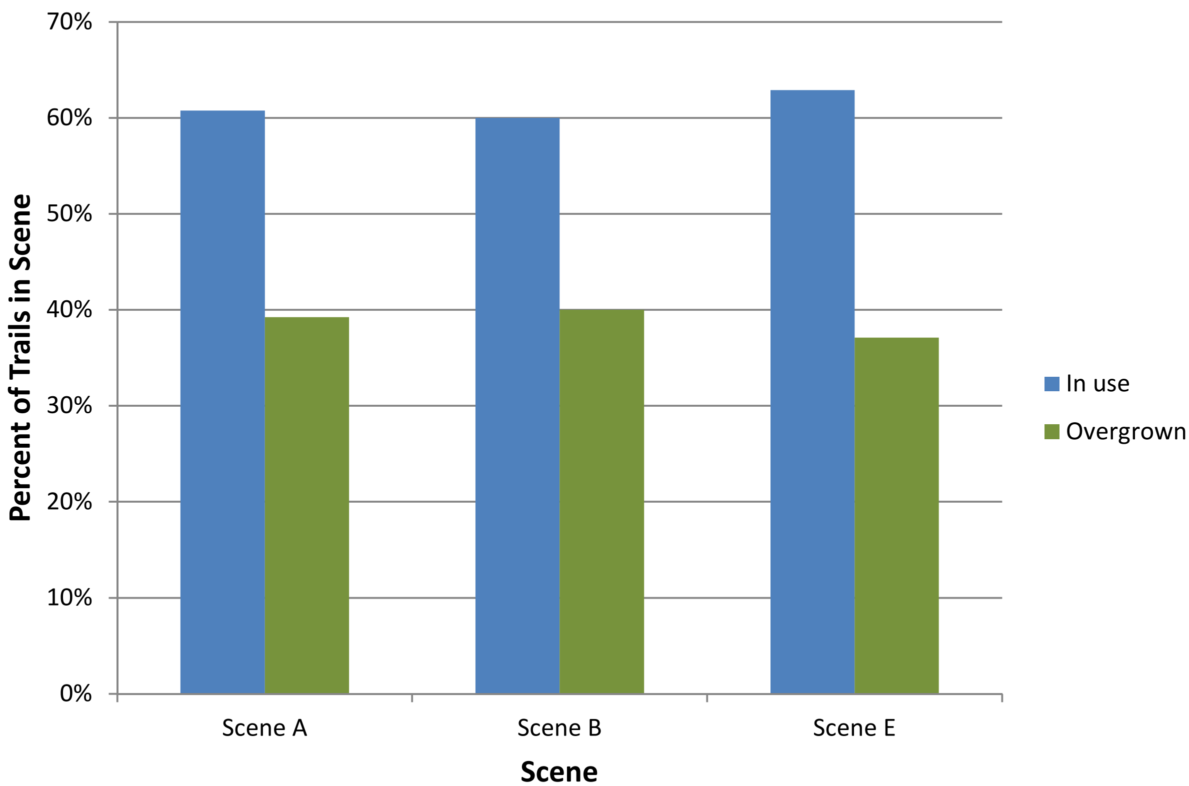
3.2.2 Use Summary

Subsequent to the modifications made to the existing trails datasets for scenes A and E, the model score for each trail was summarized (see Section 2.7). Based on the scores, in conjunction with a visual inspection of the imagery, the trails were determined to be either overgrown or active. The use classes were then summarized for each of the SPOT scenes. The results are fairly consistent across the three scenes: approximately 60% of the trails are active and 40% appear to be overgrown (Table 6 and Figure 14).

Table 6. Percent of Trails by Use Class

Scene	In Use	Overgrown
Scene A	60.8%	39.2%
Scene B	60.0%	40.0%
Scene E	62.9%	37.1%

Figure 14. Percent of Trail Use Class by SPOT Scene



3.3 Polygonal Features

3.3.1 Data Modifications

The polygonal features (e.g., wellpads, pipeline right-of-ways) in scenes A and E were also reviewed and modified as required using a similar approach to the roads and trails. Table 7 summarizes the number of modifications made to the existing digital datasets to update the polygonal features for scenes A and E. Table 8 and Figure 15 detail the percentage of features by modification type.

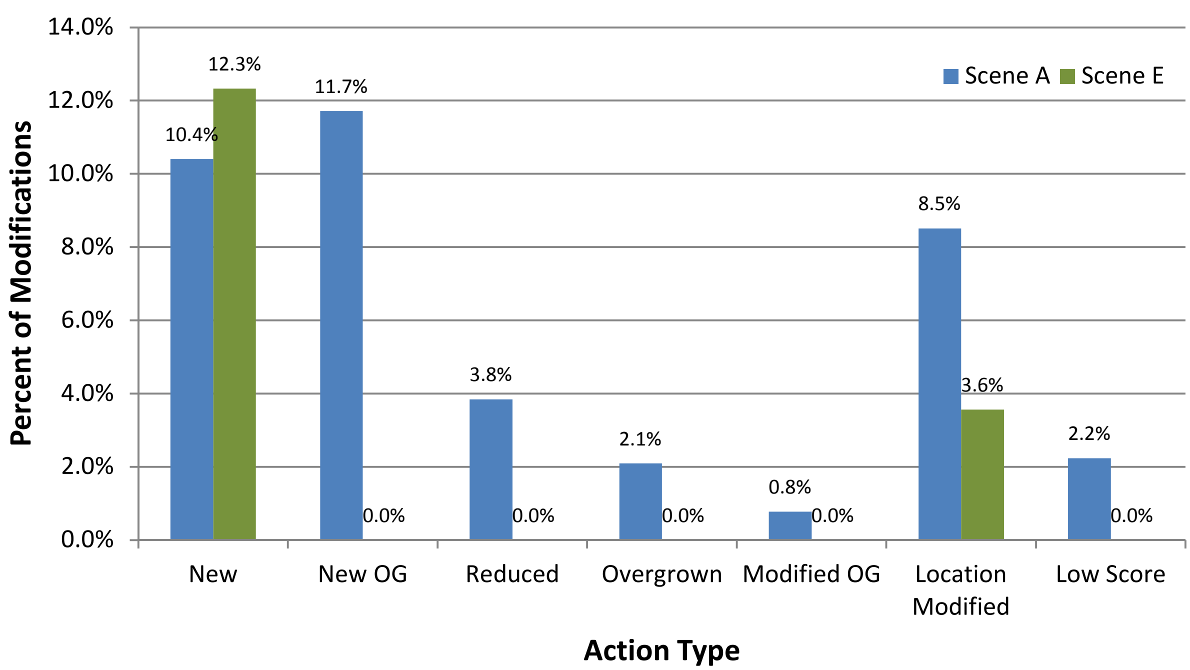
Table 7. Number of Polygonal Features Assigned to each Action Class

Scene	None	New	Missing Overgrown	Reduced	Overgrown	Location Modified	Low Score	Grand Total
Scene A	1,243	214	257	79	43	175	46	2,057
Scene E	1,228	180	0	0	0	52	0	1,460
Grand Total	2,471	394	257	79	43	227	46	3,517

Table 8. Percent of Polygonal Features Assigned to each Action Class

Scene	None	New	Missing Overgrown	Reduced	Overgrown	Location Modified	Low Score
Scene A	60.4%	10.4%	12.5%	3.8%	2.1%	8.5%	8.5%
Scene E	84.1%	12.3%	0.0%	0.0%	0.0%	3.6%	3.6%

Figure 15. Percent of Modifications to Polygonal Features by Action Type



The results related to polygonal features vary between the two scenes: 60.4% of the features in Scene A required no modification compared to 84.1% for Scene E. The most significant changes as they relate to the development of an up-to-date dataset for polygonal features concerned:

- Over 10% (10.4% in Scene A and 12.3% in Scene E) of the polygonal features were missing from the existing digital datasets.
- In Scene A, a significant number of features were not in the correct location: 8.5% had to be repositioned compared to 3.6% in Scene E.
- Relatively few (2.1% in Scene A and 0.0% in Scene E) of the polygonal features have become overgrown. However in Scene A, 11.7% (241 features) overgrown features had to be added to the dataset. Potentially these features had been removed from the current versions of the source datasets because they were overgrown; however, from a cumulative effects perspective these features should be maintained to enable the dataset to be multi-temporal.
- In Scene A, the footprint associated with 79 features (3.8%) was reduced to reflect the spatial extent present in the imagery. This is probably a function of the as-built versions of the proposed development footprints having not been submitted and/or updated in the datasets.

3.3.2 Use Summary

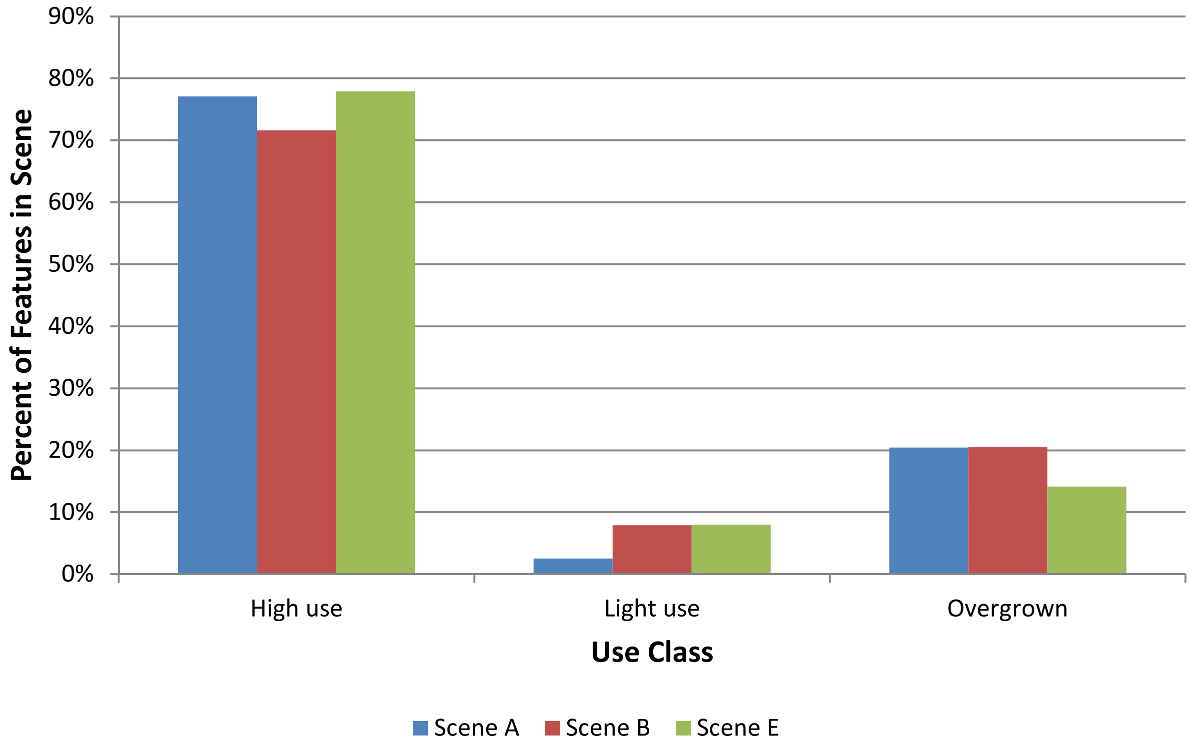
Subsequent to the modifications made to the existing polygonal datasets for scenes A and E, the score for each polygon was summarized to quantify the proportion of the feature being captured by the model. Based on the model scores, in conjunction with a visual inspection of the imagery, the polygons were determined to fall into one of three use classes: high use, light use or overgrown. The use classes were then summarized for each of the SPOT scenes (Table 3 and Figure 16).

The results are fairly consistent across the three scenes: approximately three quarters of the polygonal features are high use (71.6% to 77.9%), less than 10% (2.5% to 8.0% of the features fall into the light use class and approximately 20% (14.1% to 20.5%) appear to be overgrown (Table 9 and Figure 16).

Table 9. Percent of Polygonal Features by Use Class

Scene	High Use	Light Use	Overgrown
Scene A	77.1%	2.5%	20.4%
Scene B	71.6%	7.9%	20.5%
Scene E	77.9%	8.0%	14.1%

Figure 16. Percent of Polygonal Feature Use Class by SPOT Scene



3.4 Assigning Use Classes to Cutline Features

The results derived from the analysis of the model results for the other linear feature types (e.g., roads and trails) were used to classify the cutlines according to use type. Table 10 summarizes the number of cutlines falling into each use class and Table 11 details the percent falling into each class. The results for the three SPOT scenes are relatively consistent: just less than half of the cutlines are relatively new (ranging from 37.1% in Scene E to 48.4% in Scene A); approximately one third are partially overgrown (28.2% to 39.9%) and approximately one quarter (16.8% too 25.6%) are overgrown.

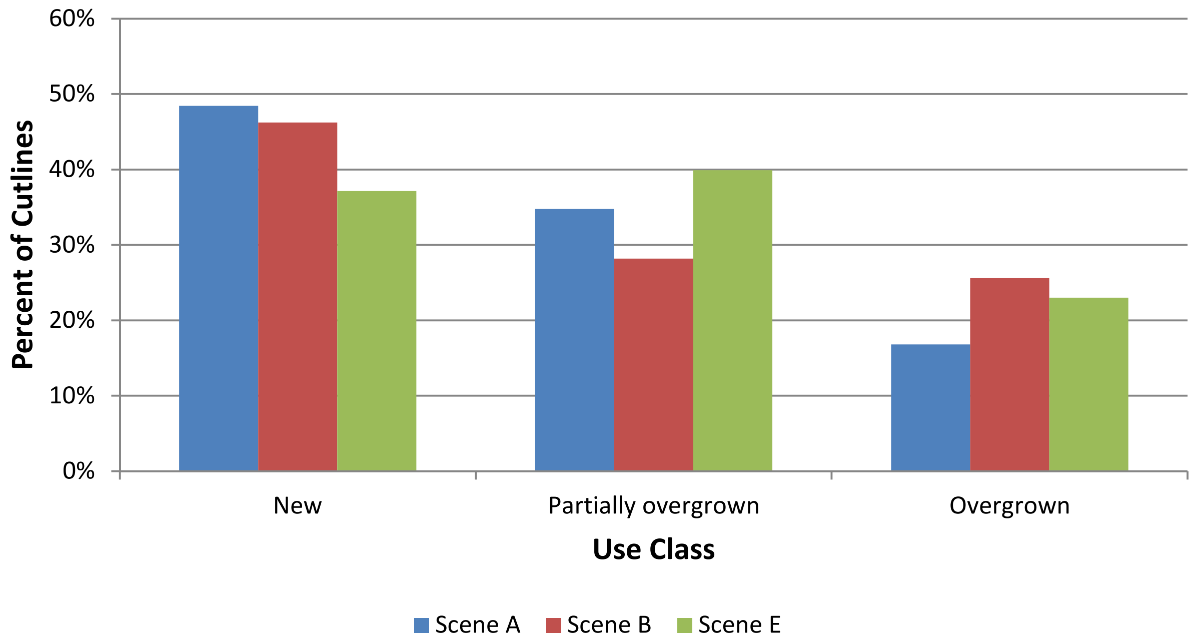
Table 10. Number of Cutline Features by Use Class

SPOT Scene	New	Partially overgrown	Overgrown	Grand Total
A	33,417	23,974	11,609	69,000
B	45,596	27,792	25,223	98,611
E	9,239	9,926	5,720	24,885
Grand Total	**88,252**	**61,692**	**42,552**	**192,496**

Table 11. Percent of Cutline Features by Use Class

SPOT Scene	New	Partially Overgrown	Overgrown
A	48.4%	34.7%	16.8%
B	46.2%	28.2%	25.6%
E	37.1%	39.9%	23.0%

Figure 17. Percent of Cutline Features by Use Class for each SPOT Scene



4.0 KEY FINDINGS AND RECOMMENDATIONS

4.1 Key Findings

Completion of the project resulted in the following findings:

- The model facilitates a semi-automated approach to the capture of new disturbance features. In some areas the model could be used to derive mapped features directly (i.e., through conversion of the raster data to vectors). However, in areas with only a few missing features it would be more practical to manually update the vector dataset by heads-up digitizing the missing features.
- The model makes it much easier (and therefore cost effective) to update human disturbance data because missing features are much easier to identify.
- The results of the pilot project indicate that use levels can be assigned to features to help quantify the amount of active human disturbance present in the landscape.
- The model is extremely effective at identifying the active footprint associated with disturbance features.

4.2 Recommendations

The following recommendations should be considered:

- The results should be verified in the field. Ideally, photos should be taken with an associated GPS coordinate and accompanying descriptive text indicating the direction of the photo. These photos could then be linked to specific locations to facilitate a more detailed evaluation of the model and subsequent refinement of the results.
- The model results could be used to identify and map wildlife movement corridors for different species. In effect the model allows 'low cost' movement pathways to be identified. These pathways could be used to evaluate prey/predator relationships which is of particular relevance to boreal caribou in this area.
- The model allows the accessibility of given areas to be better quantified through the identification of active trails, rough roads and seismic lines that facilitate human access.
- The results of the model could potentially be used to monitor the success of reclamation efforts because areas of vegetation regrowth can be quantified easily.
- It would be worthwhile to conduct a pilot project to examine how the model could be used to more effectively identify linked pathways in the data (i.e., improve the connections between linear features to yield a seamless, connected transportation/disturbance network).
- Scenarios for different time periods could be developed through the acquisition and classification of imagery for given years. This would result in a multi-temporal dataset that would be of relevance in cumulative effects assessment.