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Characterizing a Decade of Disturbance Events using Landsat and MODIS Satellite Imagery in Western Alberta, Canada for Grizzly Bear Management

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Abstract

Mapping and quantifying the area and type of disturbance within forests is critical for sustainable forest management. Grizzly bear (*Ursus arctos*) have large home ranges and diverse habitat needs and as a result, information on the extent, type, and timing of disturbances is important. In this research we apply a remote sensing based disturbance mapping technique to the southeastern extent of grizzly bear range. We apply a data fusion approach with MODIS 250m and Landsat 30m spatial resolution imagery to map disturbances biweekly from 2001-2011. A regression tree classifier was applied to classify the disturbance events based on spatial and temporal characteristics. Fire was attributed based on a national fire database. Results indicate across the 130,727 km^2 study area 4,603 km^2 of forest were disturbed over the past decade (2001-2011) impacting 0.35% of the study area annually. Overall, 68.7% of the disturbance events were attributed to forest harvest, followed by well sites 13.4%, fires 9.3% and road development, 8.6%. Primary source habitat contained 3.8% of disturbed land, and primary sink areas had 5.9% disturbed land. Our findings quantify habitat change which can aid managers by identifying significant areas for grizzly bear conservation.

1. Introduction

Sustainable forest management aims to maintain biodiversity, ecosystem structure, and ecosystem services (Amoroso et al. 2011) while allowing persistence of renewable resources for future yield. Forested ecosystems are highly dynamic and often subject to a wide range of disturbances which can include both biological (e.g., disease, insects) and non-biological (e.g., fire, wind throw) events as well as anthropogenic disturbances including mining, forest harvest, road building and infrastructure development (Nielsen et al. 2004a). Fire and forest harvest, given time, will return back to a natural state, whereas roads or well sites represent more permanent changes and are often viewed as habitat loss (Roever et al. 2008). Disturbances can cause mortality to organisms and alter the spatial fragmentation of the landscape, with potentially significant impacts on wildlife habitat (Gardner 1998, Nielsen et al. 2004b). The amount and extent of fragmentation, available and edge habitat quality, and resource availability are closely related to disturbance regimes and influence forest productivity and biodiversity (Berland et al. 2008; Linke et al. 2005).

Western Alberta Canada is a dynamic area with widespread resource extraction activities (Roever et al. 2008). Increased coal, oil, gas, and timber extraction, in addition to local population growth and subsequent urban expansion and development, impacts biodiversity through habitat loss and fragmentation (Schneider et al. 2003). Western Alberta represents the eastern limit of grizzly bear (*Ursus arctos*) habitat in southern Canada and the last of its historic range in the province (Nielsen et al. 2009). Grizzly bear within the area occur at low densities due to their extensive habitat demands. On the east side of the rocky mountain massif, grizzly diet consists mainly of plant resources (*Equistem* spp.,*Trifolium, Vaccinium* spp., *Rubus* spp., etc.) with a small proportion of ungulate protein and insects, varying amongst populations (Munro et al. 2006). The size of individual home ranges is determined by sex (Gau, 1998; McLoughlin et al. 1999), age, reproductive status, and resource availability (McLoughlin et al. 2000). Grizzly bear have low reproduction rates, caused by the age at which they reach reproductive maturity, number of offspring produced, dependency of cubs on the mother for resources and protection, and long intervals between litters (Alberta Grizzly Bear Recovery Plan, 2008). Based on population inventory data (2004-2008) and concerns over habitat alteration, the status of this species was changed to “threatened” in 2010. Resource extraction in western Alberta increases the area of habitat alteration and the number of grizzly human-bear interactions, which is the greatest cause of mortality for bears (Nielsen et al. 2009). Grizzly bear require a mosaic of landscapes that had been historically maintained by wildfires. Because of effective fire suppression and increased resource extraction, anthropogenic disturbances have partly replaced the role of fire in providing this variation in habitat (Bratkovich, 1986, Hillis, 1986; Nielsen et al. 2004b, c). Forest regeneration and edge habitats provide a range of herbaceous plants and shrubs that are important forage for grizzly bear (Nielsen et al. 2004a) and thus can, depending on the time since disturbance, provide beneficial habitat for bears. However roads connecting industries to the resources themselves, create increased probabilities for bear–human interactions (Berland et al. 2008, Nielsen et al. 2004a, 2008), and are therefore a major factor in bear mortality. Comprehensive management plans therefore need to recognize and map natural and anthropogenic disturbance while at the same time minimizing human bear interactions. One possible method of mapping disturbances in a timely and spatially comprehensive way is through satellite remote sensing. Remote sensing offers potential to detect and attribute disturbance events across large areas. For instance, the Landsat series of satellites have proven capable of observing land cover change at 30 m spatial resolution for over 40 years. However, Landsat has a revisit time of 16 days which, together with frequent cloud cover, limits timely attribution of disturbances (Wulder et al. 2008a), although increasingly numerous approaches for mitigating cloud cover have emerged (Kennedy et al. 2007; Huang et al. 2010; Wulder et al. 2011; Griffiths et al. 2013). One potential approach to mitigate this limitation is by fusing Landsat imagery with other satellite data having a shorter revisit time, such as the data blending approach of Gao et al. (2006). We use the Spatial Temporal Adaptive Algorithm for mapping Reflectance Change (STAARCH) (Hilker et al. 2009) to derive disturbance patches based on biweekly surface reflectance data at 30m spatial resolution. STAARCH uses combined Tasseled Cap Transformations (TCT) of Landsat Thematic Mapper (TM)/ Enhanced Thematic Mapper Plus (ETM+) and Moderate Resolution Imaging Spectrometer (MODIS) imagery. While this technique has been successfully applied to map disturbances across large areas, remotely sensed disturbance maps may also be used for disturbance attribution. One possible way to attribute disturbance patches is by their shape and time of occurrence. That is, anthropogenic disturbance patches can be characterized by their regularity in shape and limited spatial extent, whereas non-anthropogenic disturbances tend to be more irregular or variable in shape (Stewart et al. 2009). In our previous work, Gaulton et al. (2011) applied the STAARCH approach to examine 7 years of disturbance across the region validating the estimates using a yearly Landsat-based change sequence. Producer's accuracies ranged between 15 – 85 % (average overall accuracy 62 %, kappa statistic of 0.54) depending on the size of the disturbance event.

In this paper we extend this work in three critical ways. First we extend the size of the area of interest to cover the complete area of grizzly bear source and sink areas. Second we temporally extend the approach to cover a decade of change in the region. Finally, we attribute the detected disturbance events as forest cutblocks, fire, well sites or roads using a series of rules defined within the study area. This unique combination of the increased focus area, the extended time period and the attributed disturbance types, we believe provides the most comprehensive, analysis of the disturbance regime in the area. To do so, we our approach was as follows. First, disturbance events were detected using the STAARCH approach. A decision tree approach was then applied to attribute disturbance events based on both spatial and temporal characteristics allowing us to assess how much of this disturbance is anthropogenic or non-anthropogenic in nature. We distinguished between forest harvest, resource exploration and installations, and road development, as well as fire disturbance based upon polygons from the national fire database. Classifying disturbance by type allows anthropogenic change to be quantified and the persistence of cover change to be calculated. We examine disturbance regimes across the entire region, by season and by type. Lastly, to demonstrate how these data can be used, we compare disturbance events with Grizzly bear habitat states (Nielsen et al. 2005) to observe spatial patterns of disturbance with safe harbor and attractive sink habitats. Our observations aim to provide an indication of how these datasets can be used to fill missing elements to grizzly bear comprehensive management strategies, which is quantifying habitat loss and bear-disturbance interactions that can be applied over large areas.

2. Methods

2.1 Study Area

The foothills region of Alberta, Canada, is a transition zone between the Rocky Mountains and Prairies, with elevations ranging from 700-1700m above sea level. The 130,727 km^2 study area is typified by a wide range of temperature conditions (average temperature -12 to 15 ° C). Forests in the lower elevations in the foothills region are deciduous or mixed wood and common tree species include aspen (*Populus* spp.), balsam poplar (*Populus balsamifera*), white birch (*Betula papyifera*), lodgepole pine (*Pinus contorta*), white spruce (*Picea glauca*) and black spruce (*Picea Mariana*). The upper elevations in the foothills region is characterized by a distinct change in tree species dominance from mixed or deciduous to closed conifer forests of primarily lodgepole pine (Natural Regions Committee 2006). The region has been sub divided into five Grizzly bear habitat states: non-critical, primary sink, secondary sink, primary and secondary habitats (Nielsen et al.

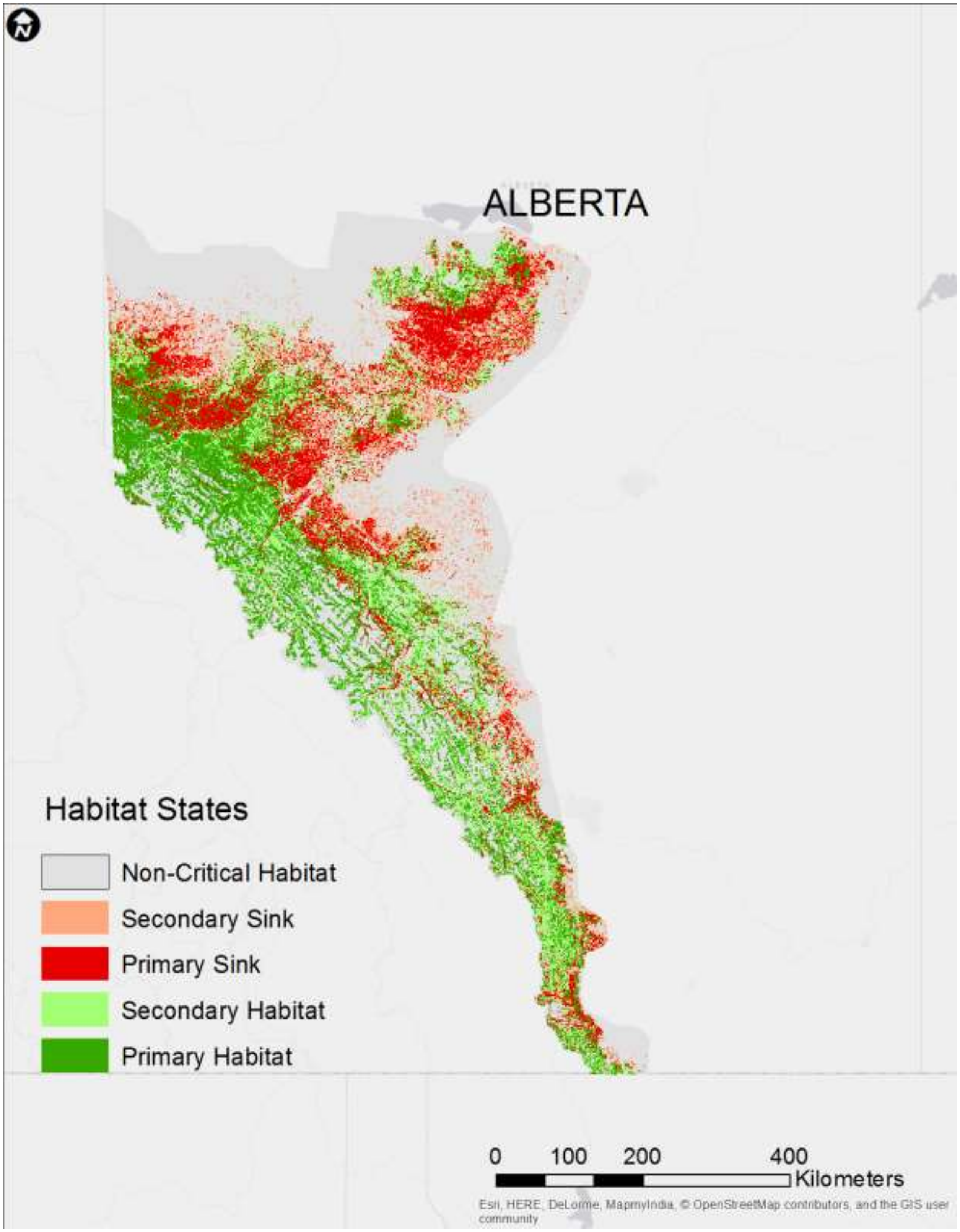

Figure 1: Study area in Alberta showing the foothills area with observed Grizzly bear habitat states.

2006) the states indicate whether areas are important to grizzly bear and if there is an increased chance of conflict or mortality (sink areas).

2.2 Data

2.2.1 Disturbance Detection

The STAARCH algorithm relates biweekly change in forest cover at 30m spatial resolution (Hilker et al. 2009). In brief, the algorithm utilizes a minimum of two Landsat observations of the same location at the start and end of the study period, in addition to a sequence of MODIS 250 m images at a biweekly interval (Gao et al. 2006). First, the spatial extent of disturbances occurring from one Landsat observation to the next is mapped using two or more cloud filtered (Irish et al. 2006) scenes. Disturbances are mapped using a spectral disturbance index (Healy et al. 2005) based on the brightness, greenness, and wetness indices following calculation of the TCT (Kauth and Thomas, 1976). Second, a time series of MODIS imagery is used to determine the time of disturbance at biweekly time steps. To do so, the MODIS based disturbance index is computed based on the MODIS land bands and compared to identify significant changes in the time series of bi-weekly observations. The STAARCH algorithm has been applied and validated in previous research within the same study area (Hilker et al., 2009). This work demonstrated the accuracy and applicability of the STAARCH based disturbance detection technique, for identifying and categorizing disturbance based on spatial and temporal metrics. Hilker et al., (2009) found the STAARCH approach had an accuracy rate for correctly identifying disturbances in the correct year of 87%, 87% and 89% in 2002, 2003 and 2005 respectively, based on an independently derived disturbance mapping dataset derived from aerial photography. The spatial accuracy of the detection area itself was 93% when compared to the validation dataset. Areas where the algorithm had poorer accuracy were wetter sites, and as a result, disturbances within flood plains and bogs, may be more poorly represented. Similarly successful disturbance detection is dependent on cloud free viewing, so in some cases there was an 8-day delay in time attribution due to cloud obscured MODIS data. Overall however, we are confident in the accuracy of the approach and its applicability for assessing and attributing disturbances in this region. As persistent cloud and snow cover makes delineation of disturbance events extremely difficult in winter, the STAARCH methodology is applied only to growing season images (March to October). As a result, areas disturbed in winter will appear in the first image in the growing season of the following year (Hilker et al., 2009).

For this project a total of 64 Landsat 5 TM scenes covering an area of 16 path/rows (Table 1), acquired between July 2001 and August 2011 were obtained free of charge and ready for analysis (Woodcock et al. 2008) from the USGS GLOVIS archive (http://glovis.usgs.gov/). Images were selected to minimize cloud cover (where possible to below 30%) as well as the temporal separation between adjacent scenes across the study area. All images were expressed as top of atmosphere reflectance and corrected using a dark object subtraction (Song et al. 2001) technique. Land cover data was obtained from the Landsat 7 land cover classification of Canada that was produced for the Earth Observation for Sustainable Development of forests (EOSD) initiative (Wulder et al. 2008b) representing circa year 2000 conditions.

Table 1: the location and the date of acquisition of the Landsat images used in the research analysis, obtained from the USGS GLOVIS archive

Path	Row	2001	2004	2008	2011
41	26	2001-10-03	2004-06-21	2008-09-20	2011-09-29
42	24	2001-09-08	2004-07-14	2008-07-25	2011-08-10
42	25	2001-09-08	2004-07-14	2008-07-25	2011-09-04
42	26	2001-09-08	2004-07-14	2008-07-25	2011-09-04
43	22	2001-09-15	2004-06-19	2007-09-16	2011-09-27
43	23	2001-09-15	2004-06-19	2008-08-17	2011-08-26
43	24	2001-09-15	2004-06-19	2008-08-17	2011-08-26
43	25	2001-09-15	2004-06-19	2008-08-17	2010-07-29
44	22	2001-07-04	2004-08-13	2008-08-08	2010-10-01
44	23	2001-07-04	2004-08-13	2008-10-11	2010-10-01
44	24	2001-07-04	2004-08-13	2008-06-21	2011-08-17
45	22	2001-08-12	2004-06-17	2009-08-27	2011-09-09
45	23	2001-08-12	2004-06-17	2008-09-16	2010-07-27
46	22	2001-09-20	2004-08-11	2008-08-06	2010-07-27
46	23	2001-09-04	2004-08-11	2008-08-06	2011-08-31
47	22	2001-08-10	2004-08-18	2008-09-14	2011-09-07

2.2.2 Disturbance Attribution

Prior to attribution, any disturbance patches which had adjacent disturbance patches detected at the same date were merged by Date of Disturbance (DOD), and expanded until no more adjacent polygons exist. Patches less than one hectare in size were removed based on Hilker et al. (2011). Fragstats, a landscape ecology tool that calculates intra- and interpatch metrics, was used to obtain the necessary spatial analytics (McGarigal et al. 2012). A simple way of defining patches is by using any contiguous disturbed area. The patches are then used to calculate area and shape specific parameters including area/density/edge metrics, shape metrics, core metrics, isolation/proximity metrics, contrast metrics, contagion/interspersion metrics, connectivity metrics, and diversity metrics (Su et al 2011). Patches are defined as groups of pixels surrounded by null space. Three sets of metrics were calculated for each patch including area, perimeter, contiguity and perimeter-area ratio. Core area and core area index, were also calculated and can be used to quantify the area that is not under edge influence. Lastly, isolation and proximity metrics calculate the distances between nearby patches (Hilker et al 2011).

A decision tree model previously developed by Hilker et al (2009) was then applied using the patch characteristics to identify disturbance type. Decision trees use data mining approaches to find the most accurate predictive method based on patterns within large datasets. As described in Hilker et al (2009), the key patch metrics identified as the most important variables in disturbance prediction were date of disturbance (DOD), core area (Core m^2), patch area (Area m^2), core area index (CAI), and contiguity index (Contig), described in Table 2. Core area and patch area allow separation between the relatively small well sites and larger fires, while CAI and contiguity indices are indicative of the disturbance shape, separating regular shaped harvest areas from elongated roads or irregular shaped fires.Patch characteristics combined with the DOD were used to classify well sites, roads, and forest harvest between 2001 and 2011 using decision tree analysis. In addition to the automatic attribution of the polygons, we utilized the Canadian National Fire Database and the Alberta ESRD Historical Wildfire Perimeter Data. The two datasets provide perimeter data for the outer limits of individual fires within Alberta, based on satellite imagery. Data completeness varies between year and collection agency, and the methods of different mapping techniques. Fire polygons were used to dictate the fire attribution of intersecting STAARCH polygons with the remainder classified as either well site, road, fire, or forest harvest.

2.2.3 Grizzly Bear Habitat States

The habitat states for the study area were created from the methods derived in Nielsen et al. 2006, which combined the relative probability of adult female occupancy (based on environmental variables and telemetry data (Nielsen et al. 2005), and risk of human caused mortality (based on bear mortality data) (Nielsen et al. 2004a) models. From these models Nielsen et al., (2004a) then derived sink (Delibes et al. 2001, Naves et al. 2003) and safe-harbor (source) areas and extended them across the complete study area of western Alberta. Attractive sinks are areas where grizzly bears were likely to occur, but are at higher risk of human-caused mortality. Safe-harbor sites are areas where grizzly bears are likely to occur, with a lower risk of human-caused mortality. Habitat states were divided into five separate groups calculated from the above methods; primary and secondary habitat (sources), primary and secondary sink (sinks) and non-critical habitat (Nielsen et al. 2006).

2.3. Data Analysis

Our processing methodology was as follows: First the STAARCH algorithm was applied to identify disturbance patches. These patches were input into FRAGSTATS to calculate the required metrics for use in the decision tree developed by Hilker et al. (2011) to attribute each patch as either well site, road or forest harvest. The fire disturbance layer was then overlaid with the patch identification layer produced from STAARCH and the decision tree, and patches identified as fire by the fire database had their attribution changed to fire, regardless of the decision tree attribution. Polygons attributed as fire by the decision tree, but not contained within the fire polygons, were attributed to forest harvest. Disturbance polygons were then analyzed temporally (monthly and annual), for the distribution of anthropogenic and natural disturbance events. Secondly, disturbance polygons were overlaid with the grizzly bear habitat states to observe disturbance by type on known Grizzly bear habitat. We estimate confidence intervals on the disturbed areas based on the accuracy statements developed by Hilker et al. (2009, 2011). In Hilker et al., (2009) estimates of the accuracy of detecting disturbed areas is, on average, 88% . Hilker et al. (2011)evaluated the accuracy of the disturbance attribution which was between 83 – 89% .

Table 2: description of the FRAGSTATS metrics used in the decision tree model to identify type of disturbance (McGarigal et al. 2012)

Metric Name	Description
DoD	Date that change was detected from the STAARCH algorithm
Core	Area within individual patches that is greater than 30m from the patch edge
Area	Area of individual patches within the landscape
CAI	Core area divided by the total patch area multiplied by 100
Contig	Average contiguity value for cells - sum of cell values divided by number of pixels in the patch minus one, divided by the sum of the template values minus one

3. Results

3.1 Western Alberta Disturbance Attribution

Over the decade of 2001 – 2011 a total of 4,603 km^2 (± 276 km^2) of disturbances covering 3.5% of the study area were detected. Figure 2 shows the disturbances from 2001 – 2011 and disturbance type (well-site, road, fire, or forest harvest). The results show an east–west trend across the area with the Rocky Mountain region to the west having fewer disturbances than the foothills region in the east. Forest harvest accounts for most of the disturbed area between 2001 and 2011 (Figure 3). Well sites and roads were frequent, but have relatively small spatial extents (0.03 and 0.02 km^2 respectively). Fires, while more infrequent, are larger (0.26km^2) than the other disturbance types, and dominate the spatial patterns in some areas. Forest harvest occurs across the study area at differing densities and patch sizes (as related to the cut block size).

Summer (July and August) and fall (September and October) periods accounted for most of the disturbance area. The summer and fall months (July to October) have the highest proportion of forest harvesting, although sometimes decreases temporarily during dry periods due to fire risk. Road construction remained relatively consistent throughout the year; well site construction was comparatively less from June to August, and forest fires account for a variable portion of disturbance during the detection period, peaking in late summer, and early fall (Figure 4). Generally, September observed the highest amount of forest disturbance through the decade, accounting for 1,032 km^2 of disturbance (22 %), with forest harvesting accounting for 63.5% of that change.

Well sites and roads have the smallest footprint in disturbance area, averaging 0.03 and 0.02 km^2 respectively, followed by forest harvest (0.13 km^2) and fire disturbance (0.26 km^2). Non-anthropogenic disturbance (fire) has 2% of the number of disturbance events (Figure 5a) yet 9% (±0.5%) of the total area observed (Figure 5b). Well sites and roads compose 63% of the disturbance events (35% and 28% respectively), although composed only 22% (± 2%)of the total disturbed area (13% and 9% respectively). Forest harvest is 35% of the total disturbance events and occupies 69% (± 5.5%) of the disturbed area in the study area.

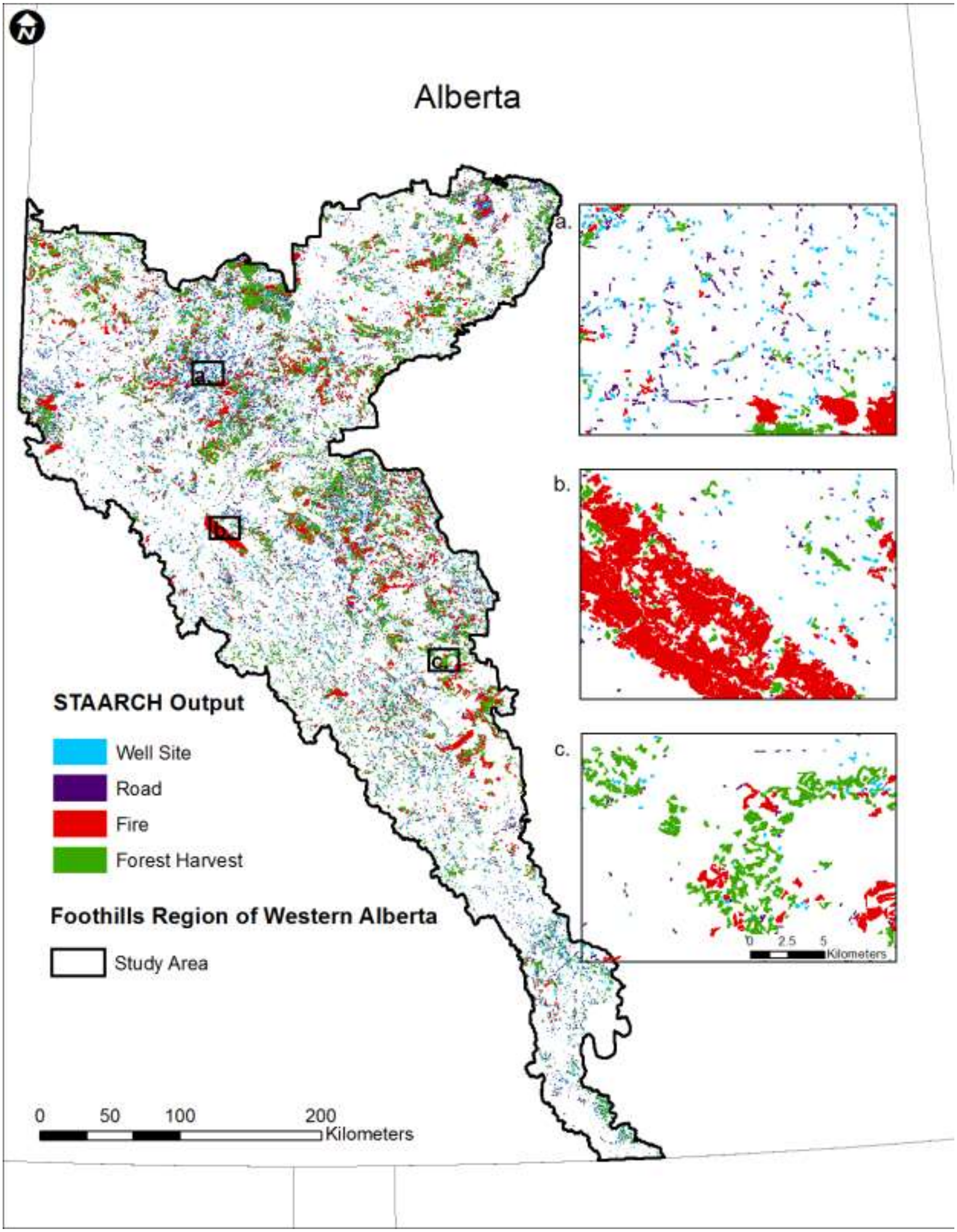

Figure 2: STAARCH output for the Grizzly bear study area classified by the type of disturbance.

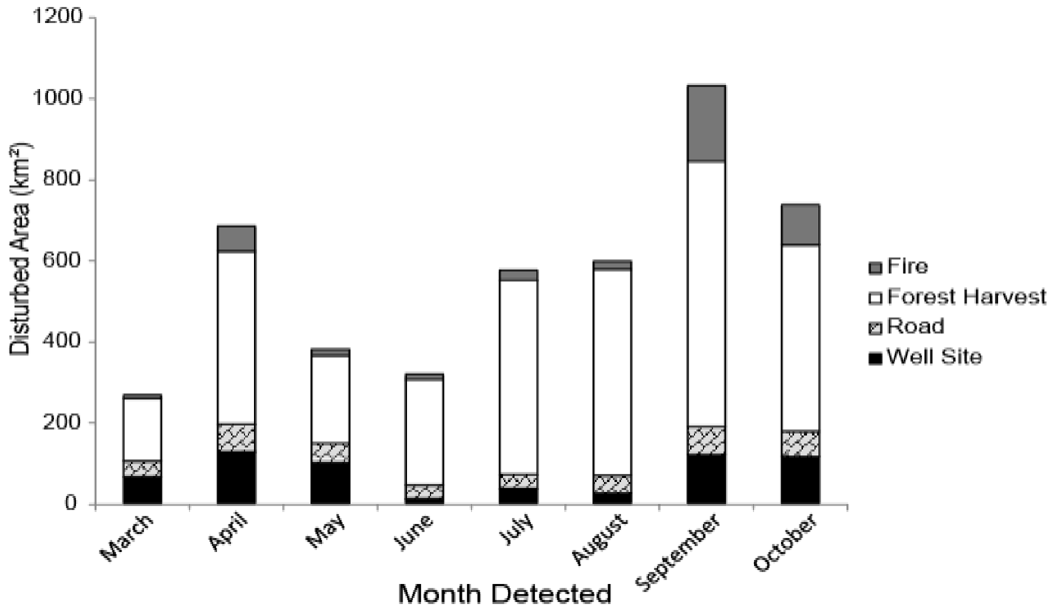

Figure 3: Total disturbed area (square kilometers) classified by the type of disturbance and by year of acquisition over a ten year period for western Alberta.

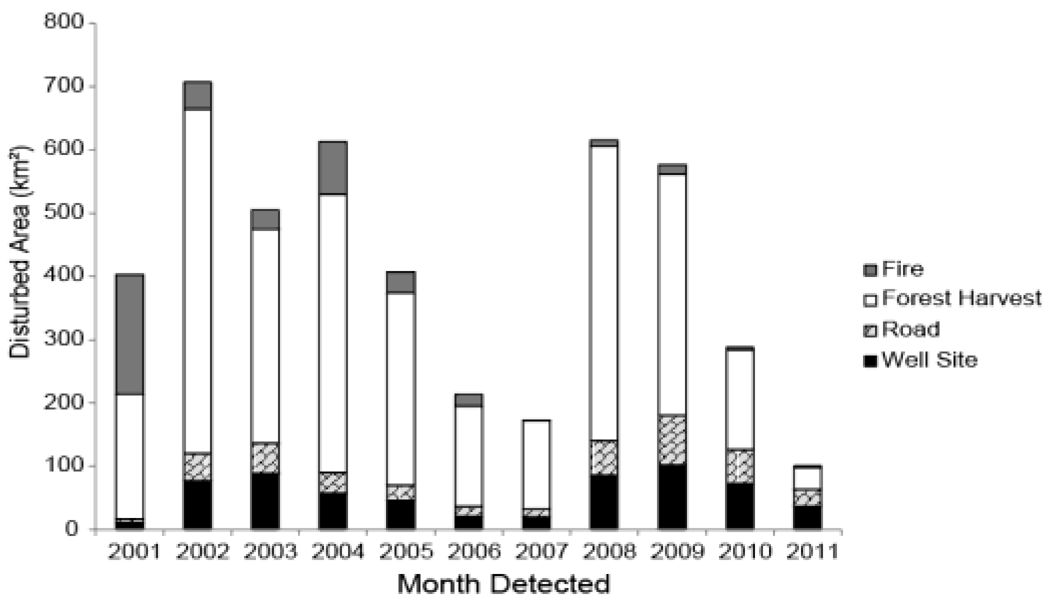

Figure 4: Total disturbed area (square kilometers) classified by type of disturbance and by month of acquisition over the ten year study period for western Alberta.

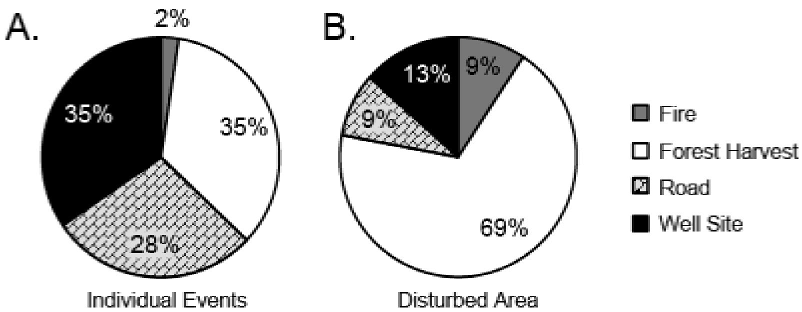

Figure 5: (A) Percent of individual disturbance events, and (B) as fraction of the area in Grizzly bear study area from 2001 to 2011.

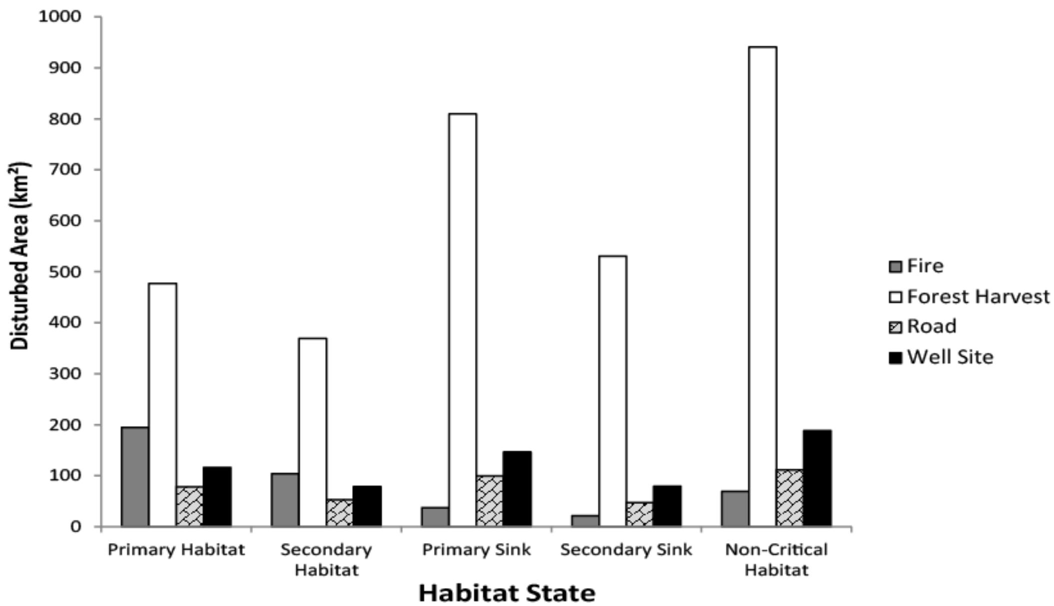

Figure 6: Total disturbed area (square kilometers) classified by type and habitat state from 2001-2011.

3.2 Habitat State Attribution

Grizzly bear source (primary and secondary) areas had lower total disturbed area than did sink areas or non-critical habitat (Figure 6). Primary habitat areas had a total of 672 km^2 of anthropogenic disturbance, and 195 km^2 of non-anthropogenic disturbance (2.9% and 0.9% of the area respectively). Secondary habitat areas had a total of 501 km^2 of anthropogenic disturbance and 104 km^2 of non-anthropogenic disturbance (2.7 and 0.6 km^2). Primary sink areas had a total of 1,055 km^2 of anthropogenic disturbance (5.9% of the area), and secondary sink areas had a total of 658 km^2 of anthropogenic disturbance (5.3% of the area). Anthropogenic disturbance is responsible for 97% of the disturbance in both primary and secondary sink habitats, and 95% in non-critical habitats. Figure 7 shows the annual area disturbed in each individual grizzly bear habitat state. Primary and secondary habitat and primary sinks, showed declining trends in disturbance area from 2001-2011, except in years 2008 and 2009 which were the highest years of total disturbance, behind 2002. Between the years of 2001-2005 total disturbed area of both primary and secondary habitat was 933km^2, compared with 539km^2 from 2006-2011. Total disturbed area for both primary and secondary sink areas from 2001-2005 was 1092km^2, and from 2006-2011 was 680km^2. Both source and sink areas show a decline in the amount of disturbed area from 2001-2011.

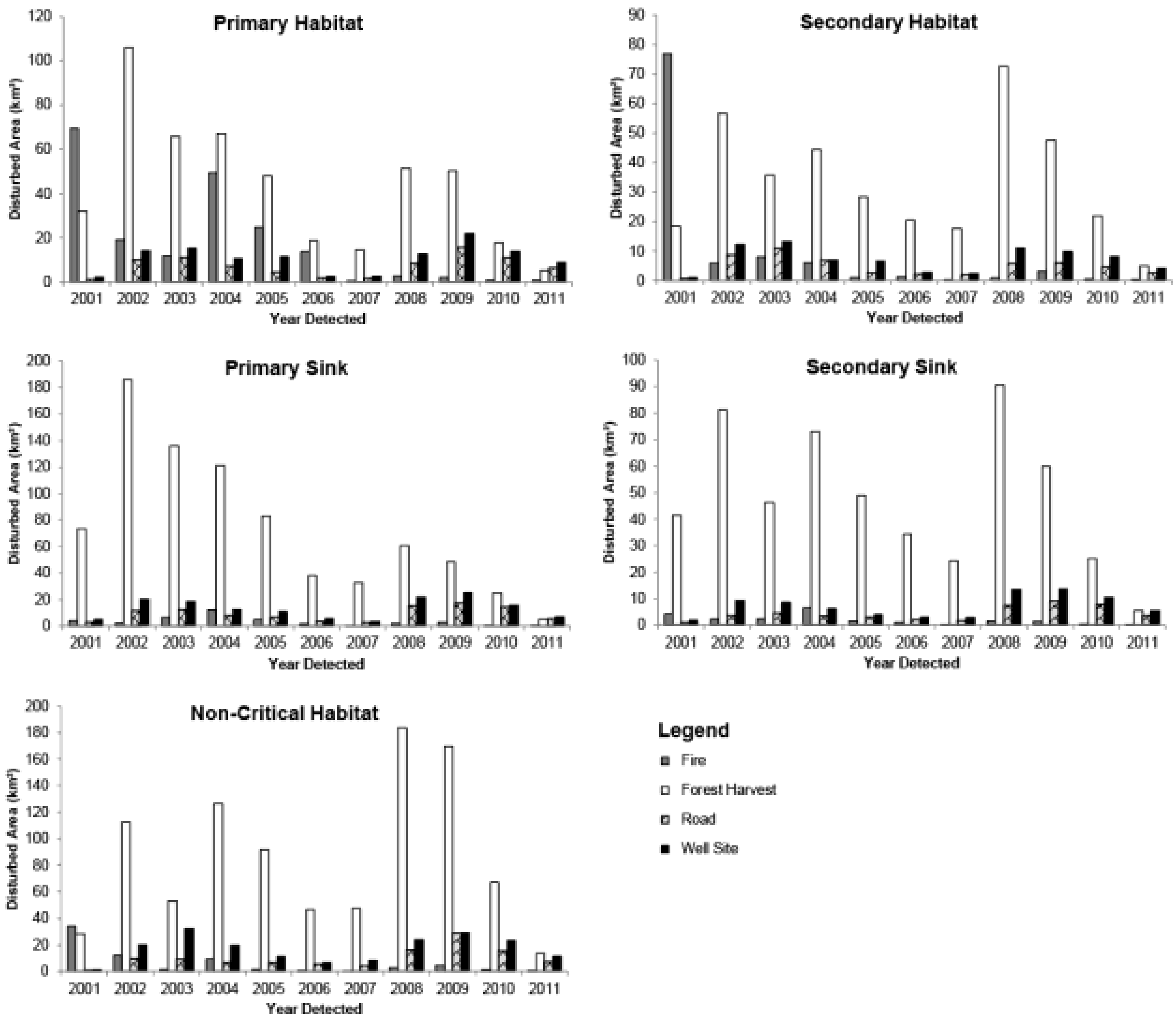

Figure 7: Total disturbed area (square kilometers) classified by year, for individual habitat states (primary habitat, secondary habitat, primary sink, secondary sink and non-critical habitat) from 2001-2011.

4. Discussion

In this paper we analyzed a decade (2001-2011) of forest disturbances in western Alberta as detected by the STAARCH algorithm for fusion of Landsat TM and MODIS satellite data. A decision tree classifier was used to attribute individual disturbances to forest harvest, fire, well sites, or roads and consequently the spatial and temporal patterns of disturbances within the context of grizzly bear home ranges were examined. While we analyzed a decade of data, 2001 and 2011 were incomplete data sets. 2001 included two time stamps, September 22 and October 8, and 2011 included time steps from the beginning of the study period until July 28.This likely reduced the total amount of area detected in these years, as well as impacting the monthly proportions over the entire study period.

Our analysis aimed to detect both anthropogenic and non-anthropogenic disturbances for western Alberta, as there is no timely, publicly available, comprehensive data source for the region on well sites, road building and forest harvest activities, derived in a consistent and transparent manner. The Canadian National Fire Database has publicly accessible historical fire polygons and these were used to allocate fire attribution on the intersecting STAARCH polygons, regardless of the decision tree results. Well sites, roads, fires and forest harvests were selected as the critical disturbance types for observation, as they represent the most common and spatially unique disturbances in the region. We applied an existing model to attribute the detected disturbances which used a unique combination of time of disturbance, as well as spatial features of the detected patch. The use of an automated change detection and attribution framework is an important goal both for remote sensing scientists as well as natural resource managers as it reduces subjectivity and improves the timeliness of change data (Stewart et al. 2009). The use of shape and contextual attributes adds additional dimensions to disturbance patches and evidence from a number of papers supports the use of shape-based and reflectance-based attributes (Stewart et al. 2009). Our approach which incorporates the temporal dimension of when the disturbance event occurred throughout the year is novel. Surface or open pit mining, pipelines, and seismic lines, also exist although these were omitted from our analysis as mines account for a small proportion of the study area only (0.55 ha/km^2; Linke and McDermid 2012). Pipelines and seismic lines were also omitted as they have a narrow disturbance footprint (Stewart et al. 2009) which cannot be reliably detected in our data fusion approach.

The rate and amount of disturbance shows a degree of agreement with other studies. Linke and McDermid report 0.62% annual rate of change/disturbance comparing well to the observations in this paper. Stewart et al (2009) identified similar levels of well site disturbance, but higher levels of road disturbances over their smaller, more industrial area. Pasher et al. (2013) in a recent study report 60% of mapped anthropogenic polygons across the whole boreal were cut blocks, followed by mines (0.9%), oil and gas infrastructure (0.1%), well sites (0.4%). The relative proportions of anthropogenic disturbances matches well with our finding. Lastly, our results attribute the area of fire disturbance at rates lower than anticipated likely due to a miss-classification with harvest. In 2003 for example, a significant fire year, the levels of area burnt detected in this study compared to the large fire database, are much lower; in some cases less than half. This suggests that fire patterns and size are similar in spatial characteristics to harvest events, a goal of sustainable forest management objectives in the area.

Gaulton et al (2011) observed 22% of disturbance events in the first two time stamps of each year using the STAARCH approach, compared with 23.4 % in this research. This may be a result of disturbances occurring outside of the study period (November-February) being recorded in the next cloud free day in the following year. Disturbance peaked in August and September, corresponding to the driest months of the year making it ideal for resource extraction (Gaulton et al. 2011). Our results peaked from September to October, with fire disturbance reaching its maximum in September. Stocks et al. (2003) found that the largest fires in Canada burned in the months of June and July. The majority of the fires have low value-at-risk and do not require intensive fire suppression, allowing for large burn areas. However, our research observed a limited area and did not cover large unsuppressed northern fires (Stocks et al. 2003).

Well sites and roads are subject to omission, due to their small area. STAARCH polygons less than one hectare in size were not included in the study, as they have a high potential for misclassification (Hilker et al. 2011) and as a result the number of events and disturbed area is likely under observed. Expanding the STAARCH polygons to join neighboring polygons resulted in an increased size of individual disturbance events. Our mean disturbance area was 0.068km^2, compared with 0.034 km^2 found by Gaulton et al. (2011) for the same study area. The overall rate of disturbance was not impacted; we observed 0.35% of disturbed land per year, compared to 0.4% in Gaulton et al. (2011).

Understanding life history traits and habitat interactions is necessary for creating comprehensive management plans for species of conservation concern (Franklin et al. 2000). Grizzly bear represent a long-lived species with expansive home ranges and low reproductive rates, with high demand for detailed management plans (Nielsen et al. 2006). We analyze habitat states to examine if our observations were in line with the model framework and general trends in disturbance rates. We confirm, as anticipate that higher percentages of anthropogenic disturbances occurs in sink habitats rather than source habitats. Higher rates of disturbance typically results in increased probability of human-bear interactions, and subsequent mortality (Nielsen et al. 2004c, 2006, 2008). The overall disturbed area of quality Grizzly bear habitat per year has declined over the past decade, but resource extraction is likely to expand further into core habitat areas (Schnieder et al. 2003)making human-bear interactions more likely (Nielsen et al. 2004a, 2006). Although anthropogenic disturbance was higher in sink rather than source areas as expected, sink areas still represent high quality habitat, but with increased risk of mortality. As the majority of grizzly bear mortality is human-caused (McLellan et al. 1999, Benn and Herrero 2002), ease of access to quality habitat areas must be reduced. Disturbances can have lasting impacts on habitats decades after the disturbance event occurs (Nielsen et al. 2004a) and some anthropogenic land cover changes (well sites and roads) represent more permanent fixtures on the landscape (Roever et al. 2008). Decommissioning of resource roads is a management objective that may have the most positive influence on grizzly bear persistence in Alberta. Understanding the impact of anthropogenically derived forest edges is another major issue given their attraction to grizzly bear, in particular in relation to food resources. A number of studies have compared grizzly bear telemetry data and edges extracted from a combination of satellite-derived land cover data and conventional vector datasets (roads, pipelines, and forest harvests). Results have demonstrated that in general female bears selected anthropogenic edges, whereas males selected natural edges and both sexes selected the natural transition of shrub to conifer (Stewart et al., 2013). Edge metrics could relatively easily be extracted from remote sensing (Wulder et al., 2009) such as in this decadal dataset, to provide fine spatial scale information for improving management of edge features and ultimately minimizing human-bear conflicts (Stewart et al., 2013). The combined use of Landsat and MODIS imagery can provide both broad scale assessment of disturbance within the major conservation zones, as well as at the stand scale for edge detection. The overall approach contributes to identifying areas of grizzly bear conservation concern, and whether or not management practices can be implemented to reduce attractive sink areas.

The STAARCH disturbance detection and attribution represents a tool for land managers to observe changes in habitat area, identify disturbance type and identify areas of conservation concern for grizzly bears. The ability to identify anthropogenic and non-anthropogenic disturbances is important for bear conservation. Anthropogenic disturbances increase the number of human-bear interactions, by creating access from resource roads into core habitat areas. Human caused mortality accounts for about 90% of bear mortality in the Rocky Mountains (Benn 1998, Craighead et al. 1988, McLellan et al 1999), therefore identifying anthropogenic disturbances can aid in bear management (Nielsen et al. 2004c, Nielsen et al. 2008). Our decade study period has the potential to be extended to observe Grizzly bear disturbance interaction over long periods. This would provide land managers with information for making better informed decisions on grizzly bear protection in Alberta.

5. Conclusion

In this paper we demonstrate the ability to map and attribute disturbances as detected by the STAARCH algorithm across the foothills of western Alberta. This is made possible by fusing fine spatial resolution of Landsat images(30m) with the high temporal resolution of MODIS (bi-weekly) images, which have lower spatial resolution of 250m. Anthropogenic disturbances (forest harvest, well sites and road construction) are the most influential disturbances on the landscape of south western Alberta, in terms of number and area affected. This disturbance has both positive (increased forage) and negative (increased human-bear interactions) implications on important grizzly bear habitat. Our research represents a viable monitoring tool for land managers through quantification the disturbed area while also characterizing the type of disturbance.

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