Chapter 16
An Approach for Determining Relationships Between Disturbance and Habitat Selection Using Bi-weekly Synthetic Images and Telemetry Data

Nicholas D. A. Brown, Trisalyn Nelson, Michael A. Wulder, Nicholas C. Coops, Thomas Hilker, Christopher W. Bater, Rachel Gaulton, and Gordon B. Stenhouse

Abstract Ecological studies can be limited by the mismatch in spatial-temporal scales between wildlife GPS telemetry data, collected sub-hourly, and the large-area maps used to identify disturbances, generally updated annually. Recent advancements in remote sensing, data fusion modeling, mapping, and change detection approaches offer environmental data products representing every 16-day period through the growing season. Here we highlight opportunities and challenges for integrating wildlife location data with high spatial and temporal res-

N.D.A. Brown
Department of Geography and Environmental Studies, Carleton University, Ottawa, ON, Canada

T. Nelson (✉)
School of Geographical Sciences and Urban Planning, Arizona State University, Tempe, AZ, USA
e-mail: trisalynnelson@asu.edu

M.A. Wulder
Canadian Forest Service (Pacific Forestry Centre), Natural Resources Canada, Victoria, BC, Canada

N.C. Coops
Integrated Remote Sensing Studio, Department of Forest Resources Management, University of British Columbia, Vancouver, BC, Canada

T. Hilker (Deceased Sep 5, 2016)
Department of Geography and Environment, University of Southampton, Highfield Rd, Southampton SO17 1BJ, UK

C.W. Bater
Forest Management Branch, Forestry Division, Alberta Agriculture and Forestry, Edmonton, AB, Canada

R. Gaulton
School of Civil Engineering and Geosciences, Newcastle University, Newcastle upon Tyne, UK

G.B. Stenhouse
Foothills Research Institute, Hinton, AB, Canada

Y. Ban (ed.), *Multitemporal Remote Sensing*, Remote Sensing and Digital Image Processing 20, DOI 10.1007/978-3-319-47037-5_16

olution landscape disturbance data sets, available from remotely sensed imagery. We integrated 16-day outputs from the Spatial Temporal Adaptive Algorithm for mapping Reflectance Change (STAARCH) disturbance maps with grizzly bear (Ursus arctos) telemetry data. Our results indicate that males and females avoided same-year disturbances, while male bears were most likely to avoid recently disturbed areas in summer. When intra-year (disturbances mapped at a 16-day time-step) analysis of disturbance was compared to traditional annual time-step analysis, annual aggregation of disturbance data resulted in an increase in the observed selection of same-year disturbed habitat, although change was not statistically significant (α 0.05). We caution the use of low-temporal resolution disturbance data to evaluate short-term impacts on wildlife and highlight the need for further development of probabilistic- and model-based techniques for overcoming spatial-temporal differences between datasets.

16.1 Introduction

Capture of forest disturbance is a critical source of information for landscape management. Traditionally, forest disturbance inventories are completed through field work or by aerial surveys at 5- to 10-year time intervals and are operationally costly and time consuming to implement over large areas. Alternatively, disturbance records may be obtained from forest managers (Nielsen et al. 2004a) or government agencies (Koehler et al. 2007); however, spatial coverage can be limited and accuracy and consistency variable when data are collected by multiple agencies for different uses. Satellite data are often also used by forest managers to provide information regarding disturbance within an inventory cycle (Masek et al. 2008). These inventory and disturbance datasets have become valuable in understanding interactions between wildlife and their environment.

Availability of satellite imagery has allowed large-area mapping of landscape disturbance (Zhang et al. 2002; Healey et al. 2005; He et al. 2009; Asner 2013). For instance, the Landsat series, first launched in 1972, has emerged as one of the most useful satellite datasets for mapping large-area disturbance due to its long temporal record (Wulder et al. 2008, 2011), relevant spectral bands for vegetation mapping, and affordability (Cohen and Goward 2004; Wulder et al. 2004). Landsat has been used extensively by geographers, ecologists, and managers to map landscape disturbance and vegetation change (Cohen and Goward 2004; Gu and Wylie 2010; Huang et al. 2010). Traditionally, large-area maps of disturbance tended to be representative of annual, or longer, time-steps (Masek et al. 2008; Cohen et al. 2010). In contrast, wildlife data, which are increasingly collected using GPS-based telemetry systems, are commonly generated with much greater frequency; wildlife locations are often now recorded on an hourly basis (Johnson et al. 2002; Sunde et al. 2009; Boyce et al. 2010). The temporal discrepancy between environmental and wildlife data has been identified as a limitation when using global positioning system (GPS) technology in ecological studies (Hebblewhite and Haydon 2010).

The opening of the Landsat archive in 2008 to provide free access to analysis-ready imagery (Woodcock et al. 2008) has enabled implementation of applications that would not have previously been practical due to image costs (Wulder et al. 2012). Notwithstanding the free and open access to all available Landsat imagery, there is a maximum possible revisit of 16 days for image acquisition. When combining the temporal revisit with the limited number of images that can be collected on any given day, for a given path/row location there is variability in the frequency of acquisition both within and between years.

The Spatial Temporal Adaptive Algorithm for mapping Reflectance Change (STAARCH) is a data fusion model that allows for the creation of high spatial and temporal resolution disturbance maps (Hilker et al. 2009). STAARCH integrates Landsat and Moderate Resolution Imaging Spectrometer (MODIS) imagery to enable mapping of disturbance at high spatial and temporal resolution. MODIS, with a repeat cycle of one (towards the poles) or two days (near the equator), is designed to provide near continuous monitoring of biophysical parameters (Justice et al. 1998; Huete et al. 2002) at spatial resolutions from 250 to 1000 m, depending on the spectral channel. A time series of MODIS images can be aggregated through compositing daily observations in order to reduce cloud contamination (Vermote et al. 1997; Hilker et al. 2009). The synthetic STAARCH product takes advantage of the high spatial resolution of Landsat and high temporal resolution of MODIS composite images to provide disturbance maps with a 16-day return interval and 30-m spatial resolution (Hilker et al. 2009; Gaulton et al. 2011).

In this chapter we examine the opportunities and challenges of integrating new high spatial and temporal resolution disturbances maps with detailed wildlife GPS data. As a case study, we integrated STAARCH disturbance maps with grizzly bear (*Ursus arctos*) telemetry data from Alberta, Canada. Using a 16-day time-step, we assessed the impact of disturbance presence and timing on spatial patterns of grizzly bear habitat selection by statistically comparing observed frequency of disturbance selection to a null hypothesis that, within available habitat, disturbances are selected randomly regardless of time since disturbance. Results from the analysis using the disturbance products with a 16-day time-step are compared with those obtained when using a single annual disturbance layer.

16.2 Study Area

The 14,000 km^2 study area is located in the foothills of the Rocky Mountains north of the town of Grand Cache, Alberta, Canada (Fig. 16.1). Terrain heights range from 600 m above sea level in the northeast to 2400 m in the Rocky Mountains towards the southwest of the study area. The landscape is characterized largely by forest cover, with forest disturbance and land use determined primarily by resource extraction industries, including forestry, mining and oil and gas (Schneider et al. 2003), with the exception of a small area in the southwest that intersects the Kakwa-Wilmore Interprovincial Park. Forests within our study area have been managed for resource extraction for over 50 years with a substantial increase since the 1980s (White et al. 2011). Given fire suppression, resource extraction and related activities are the dominant landscape disturbance, with most disturbances arising from the forest industry and oil and gas exploration (Schneider 2002). Approximately 76 %

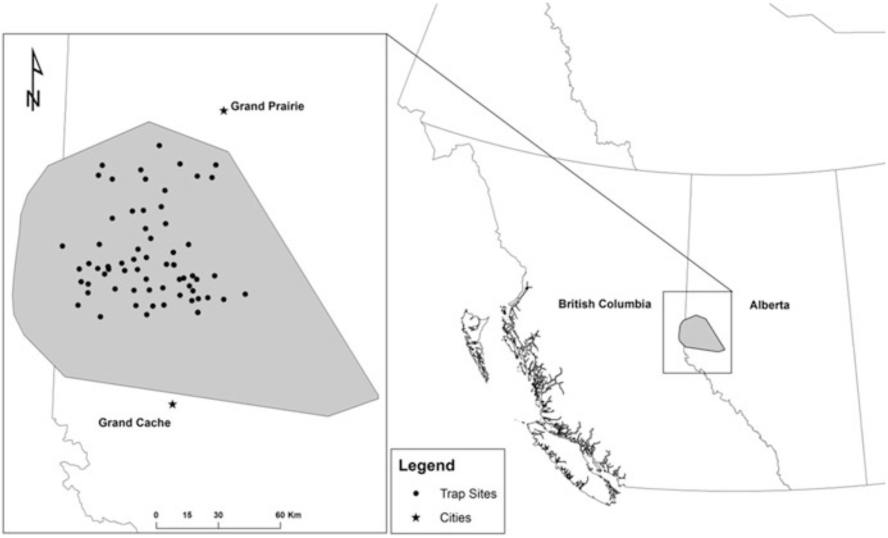

Fig. 16.1 Study area in west central Alberta, Canada

of the forested land base in the Kakwa Region is managed for timber harvesting. Forestry activities have created a patchwork of forest harvests as well as roads. The growing oil and gas industry has also led to new roads as well as pipelines and well sites. The longevity of the disturbances from resource extraction activities varies. Forest harvests will undergo vegetation succession and provide food resources for wildlife (Stewart et al. 2013). Roads that are not deactivated, pipelines, and active well sites are more permanent.

16.3 Data and Methods

16.3.1 STAARCH-Derived Disturbance

The STAARCH algorithm requires a minimum of two Landsat images to mark the beginning and end of the time period of interest (Hilker et al. 2009). The STAARCH algorithm captures disturbance using a Tassled Cap transformation of the Landsat observations, yielding a disturbance index (DI) value (described in Healey et al. 2005). A change mask is generated by thresholding consecutive DI values of a given pixel. Changes detected in the Landsat imagery are then dated using marked deviations through a time series analysis of a modified disturbance index calculated from the MODIS imagery. The STAARCH process requires MODIS 8-day composite images to create a suite of high temporal resolution disturbance indices (Zhang et al. 2002) for the time period between the first and last Landsat images. Changes in DI values for the Landsat change mask are then matched to the dates of disturbance obtained from the MODIS imagery. Preliminary results indicate that 87 and 89 % disturbances are assigned correct dates (Hilker et al. 2009) when validated against a manually verified, remotely sensed disturbance inventory (Linke et al. 2009). More recent work has reported overall accuracies of 62 %, with the lower value being attributed to a larger study area, smaller disturbance sizes, and an increased time period (Gaulton et al. 2011).

Previous research has demonstrated the Tasseled Cap Transformation (TCT) of spectral image data as a tool for effective mapping of land cover change and disturbance (Healey et al. 2005; Masek et al. 2008). The accuracy and applicability of STAARCH as a disturbance detection technique has been assessed in this study area. Using many of the same Landsat scenes as applied to this study, Hilker et al. (2009) found STAARCH 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 a disturbance mapping dataset derived independently 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.

An example of STAARCH disturbance mapping is shown in Fig. 16.2. Disturbance is defined as any event that increases the disturbance index of a previously

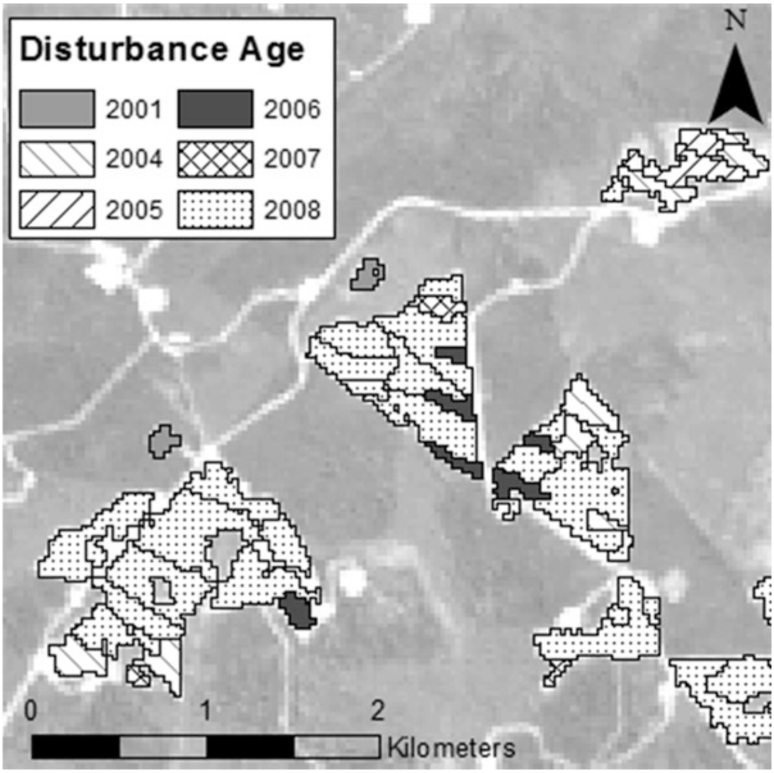

Fig. 16.2 Sample of map of disturbance created using the STAARCH algorithm. Also shown is a Tasseled-Cap-based disturbance index. *Bright pixels* indicate areas of greater disturbance

forested region as assessed by the STAARCH algorithm. Disturbances in this region are predominantly, if not exclusively, anthropogenic including forest harvests, wellsites, and roads. Disturbance mapping was conducted using a 16-day return interval and extended from September 2001 to June 2008. The modal disturbance patch size is 1.08 ha (Gaulton et al. 2011).

16.3.2 Telemetry Points

Grizzly bear telemetry data were collected using GPS radio collars attached to 40 adult (age 5+) bears. The locations of 23 male and 17 female bears were obtained between May 2005 and December 2009. The GPS collars were programmed to record a location each hour during the non-denning period (April–November), however actual recorded locations varied with individual collars. Individual bears were tracked for between one and three years. Only bears with high sampling frequencies ($\geq$10 GPS fixes/day) and $\geq$500 telemetry point locations were included, resulting in 23 total bears, 12 females and 11 males. The spatial distribution of trap locations are shown in Fig. 16.1 and the number of traps varied annually between 10 and 22.

16.3.3 Data Integration

To integrate bear telemetry data with the 16-day temporal resolution STAARCH disturbance data, we evaluated the spatial-temporal overlap between the two data sets. First, telemetry data were aggregated to represent 16-day periods to correspond with the STAARCH time intervals. For each 16-day period, the number of grizzly bear collar locations intersecting disturbance polygons was quantified, and the total disturbed area recorded by STAARCH calculated.

16.4 Grizzly Bear Response to Disturbance

We compared the observed habitat selection, recorded in the telemetry data, to expected habitat selection, based on a model to randomize telemetry data within available habitat.

16.4.1 Observed Selection

Many aspects of grizzly bear biology, such as diet and behaviour, change seasonally (Nielsen et al. 2004a, c; Munro et al. 2006), which in turn affects the spatial pattern of habitat selection (Nielsen et al. 2004a). To account for seasonal variability, disturbance and telemetry data were subdivided into: spring (den emergence to June 25), summer (June 26 to August 15) and autumn (August 16 to denning) (Nielsen et al. 2006; Smulders et al. 2012).

For each telemetry point, the nearest forest disturbance polygon was identified. Due to the availability of unique, high spatial and temporal resolution disturbance data it was possible to only consider disturbances that occurred prior to when a bear was observed when calculating nearest disturbance. Grizzly bear telemetry locations that were farther than 500 m from any disturbance were excluded from analysis. A 500 m threshold has been used previously in relating landscape disturbance to grizzly bear habitat selection (Berland et al. 2008). For each disturbance, by year, observed selection was quantified as the number of telemetry points nearest to a disturbance. Since the number of telemetry points and the sampling frequency associated with each bear was different, results were normalized by dividing the number of telemetry points associated with a particular disturbance age by the total number of telemetry points within that season.

16.4.2 Expected Selection

Observed patterns of disturbance selection were statistically compared to an expected pattern. The expected pattern or null model was that bears did not select for disturbances based on disturbance age (Smulders et al. 2010). We generated a frequency distribution of expected selection by randomizing the observed of telemetry locations within available habitat. Available habitat was defined using minimum convex polygons (MCP) that were created for each of the grizzly bears. The MCP is the smallest convex area that contains all data points (Mohr 1947) and represents the outer limit of observed habitat used by bears sampled through telemetry data collection. Ninety-nine randomizations were generated, and for each randomization the number of random telemetry points nearest to a disturbance was quantified, generating a null model for statistical comparison. Statistical results were grouped by disturbance age and presented using box plots. We defined disturbance age as the difference between the year a grizzly bear's location was recorded and the year a disturbance occurred. Disturbance age, or time since disturbance, indicates how much time has elapsed between initial disturbance and subsequent selection. The disturbance age is an indicator of forest successional stage and reflects food availability (Nielsen et al. 2004c).

16.4.3 Temporal Resolution of Disturbance Data

To assess the impact of the temporal resolution of disturbance data on research findings, we reprocessed the data for same-year disturbance with disturbance dates aggregated to an annual resolution. The effect of the temporal resolution of disturbance data on observed patterns of habitat selection was quantified by comparing the resulting annual frequency-of-selection distributions to the 16-day resolution frequency-of-selection distributions using a Komologorov-Smirnov test.

16.5 Results

16.5.1 Data Integration

In Fig. 16.3 we show the total disturbed area and total number of telemetry points that fall within disturbance polygons for each 16-day time step. In this figure we are quantifying general correspondence between all the harvest areas and telemetry data. Generally, an increase in the total disturbed area corresponds to a larger number of telemetry points within the disturbances. The number of points within the

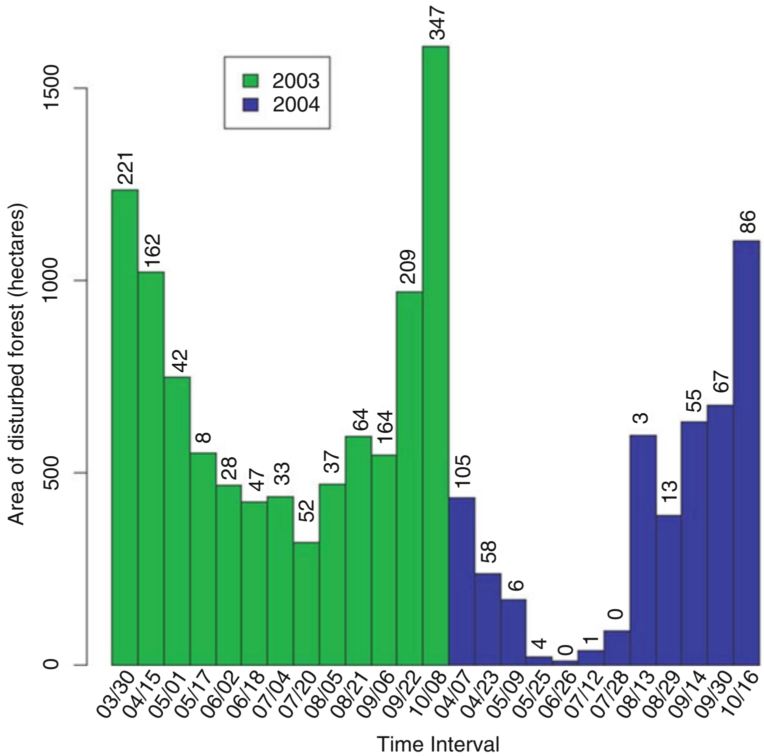

Fig. 16.3 Bar plot showing the variation in total disturbed area with time for 2 years. Numbers above bars indicate how many telemetry points fell within disturbance polygons for a given time interval (n = 99,929). All harvests are considered regardless of age, in order to show the general correspondence. As might be expected, as an area of disturbance increases there tends to be a larger number of telemetry points corresponding with disturbed locations

disturbance polygons is small relative to habitat usage; for any given time interval, the total number of points within a STAARCH forest disturbance polygon represents less than 0.005 % of the total number of points. Similarly, the total disturbed area for any one time interval is small (5.52 km^2) compared to the study area (14,000 km^2).

16.5.2 Grizzly Bear Response to Disturbance

Figures 16.4 and 16.5 show the preferential selection of disturbed habitat through time for female and male bears, respectively. For most disturbance ages, selection was highly variable, as evidenced by the large interquartile ranges. Variability

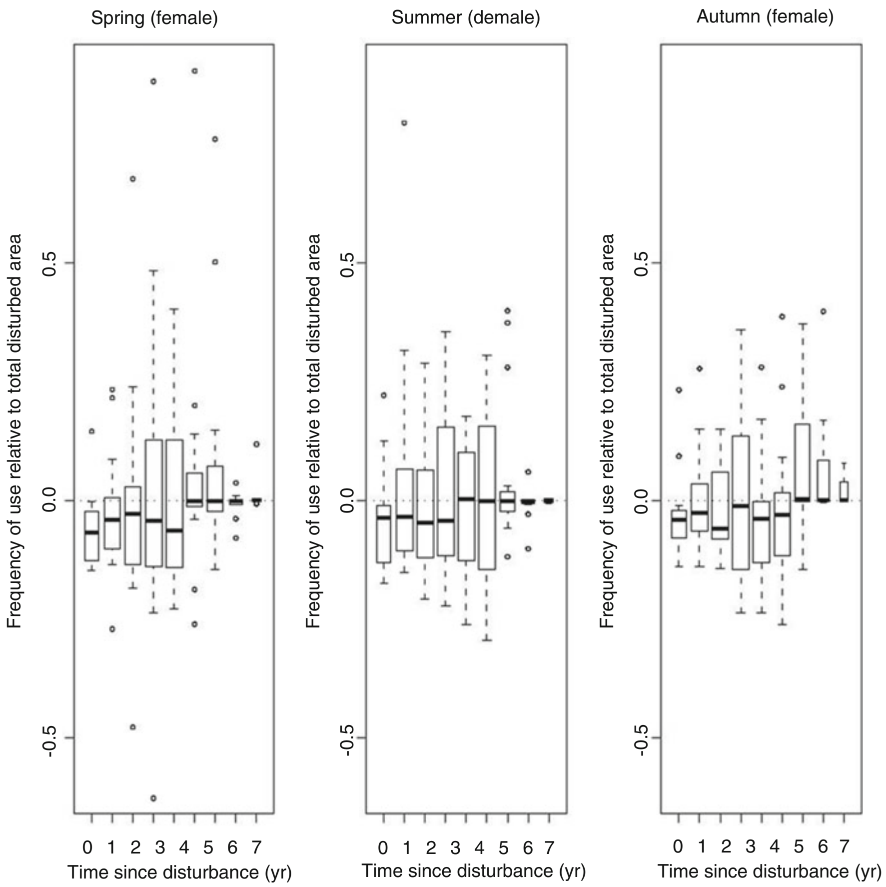

Fig. 16.4 Results for female bears grouped by season. Positive values represent selection of disturbed habitat. Negative values represent avoidance of disturbed habitat. Horizontal line at 0.0 signifies proportional selection of disturbance exactly equal to proportional disturbed area for a given year. Analysis includes 12 female bears and 53,139 telemetry locations

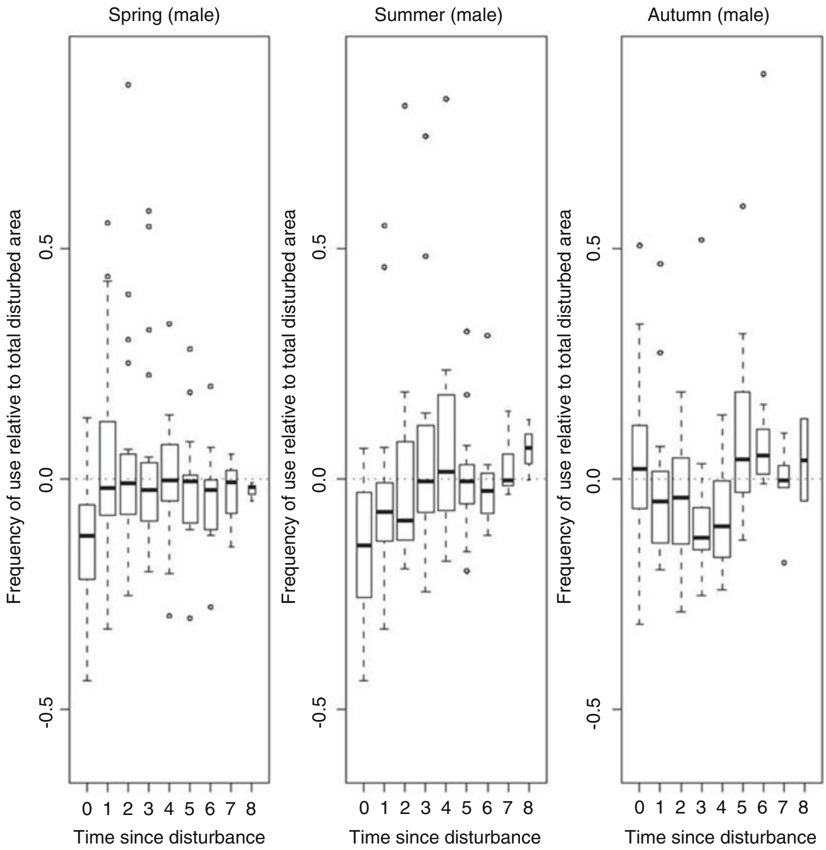

Fig. 16.5 Results for male bears grouped by season. Positive values represent selection of disturbed habitat. Negative values represent avoidance of disturbed habitat. Horizontal line at 0.0 signifies proportional selection of disturbance exactly equal to proportional disturbed area for a given year. Analysis includes 11 female bears and 46,732 telemetry locations

in selection of disturbance appeared to decline in the seventh and eighth years following disturbance, but this is likely a spurious finding resulting from smaller sample sizes (three bears as opposed to 12 or more bears).

In all seasons female bears exhibited avoidance of same-year disturbance and showed reduced selection of one- and two-year-old disturbances (Fig. 16.4). In spring, selection increased for older disturbances, with three- and four-year-old disturbances exhibiting mixed responses, and five- and six-year-old disturbances slight preferential selection. In summer, variability in selection generally increased with disturbance age up to five year old disturbances. In autumn, variability in selection increased for one-, two-, and three-year-old disturbances, and decreased for four- and five-year-old disturbances, which were generally avoided.

Table 16.1 Mean relative frequency of use for same-year disturbance. Negative values signify avoidance, whereas positive values signify preferential use. Data are presented here for 16-day STAARCH disturbance, as well as for down-sampled annual disturbance data. In every case, down-sampling of disturbance data to an annual resolution results in an increase in use

	Spring		Summer		Autumn	
	16-day	Annual	16-day	Annual	16-day	Annual
Female	−0.0625	−0.0196	−0.0409	−0.0332	−0.0276	−0.0212
Male	−0.127	−0.0403	−0.147	−0.134	0.0463	0.0573

In spring and summer, male bears exhibited slight avoidance of same-year disturbance (Fig. 16.5). During spring, selection of disturbed habitat increased slightly for one- to four-year-old disturbances, and decreased slightly for disturbances older than 5 years. For male bears in summer, older disturbances were selected more frequently than younger ones. Males in autumn were the only instance of male bears selecting for same-year disturbance. Selection of disturbance decreased for one- to four-year-old disturbance, with a minimum for 4-year-old disturbances, and then increased again for disturbances older than 5 years.

16.5.3 Temporal Resolution of Disturbance Data

In all cases, aggregating disturbance data to a yearly resolution resulted in an increase in the observed selection of same-year disturbed habitat. The difference in results was most pronounced for male bears in spring, though it was not statistically significant at the 5 % confidence interval for any of the categories (Table 16.1). Seasonal variation in the strength of trends could be due to the timing of den emergence. The sampling in spring may be less consistent as bears will emerge on different dates depending on snow pack and inter-annual variation. The summer signal may be slightly less biased by sampling.

16.6 Discussion

Our aim was to highlight opportunities and challenges of integrating high temporal resolution disturbance and telemetry data sets using a grizzly bear case study. One of the opportunities afforded by the availability of fine temporal resolution disturbance data is that the grizzly bear response to disturbance can be assessed intra-annually. Though remote sensing data have been used to investigate wildlife disturbances (e.g., Ndegwa and Murayama 2009), when disturbance data are represented annually it is not be possible to determine when within the year a given disturbance occurred on the landscape. The ability to determine when, to the nearest 16-day interval, a given disturbance occurred is an important contribution of synthetic remote sensing products such as STAARCH in support of ecological and habitat studies.

A limitation when integrating fine temporal wildlife and disturbance data sets is the often insufficient spatial-temporal overlap between the animal GPS locations and mapped forest disturbance. In some cases, when there was little disturbance proximal to a bear's location, it was impossible to ascertain how selection of disturbance changed on a same-year basis because the bear would pass through the disturbed area only once in the entire year. Another difficulty associated with data integration is that, assuming negligible error, disturbance data represent all disturbed locations. However, as a consequence of the discrete sampling through time and the practical reality of collaring a sample of individuals, telemetry points necessarily represent a sample of selected wildlife locations (Wells et al. 2011). While the remote sensing-derived disturbance data represent the statistical population of events, the wildlife data represent a sample that is relatively sparse.

Artificially downgrading the temporal resolution of the disturbance data from 16 days to one year led to results that overrepresented the selection of disturbances. When disturbance is represented annually, the nearest disturbance that occurred at any time within the year would be selected. This may be problematic if the disturbance actually occurred after the grizzly bear utilized a specific location. Although the changes in selection results were not statistically significant, this may not always be the case, particularly in areas that are undergoing high levels of anthropogenic activity. Implications for wildlife management include misinterpretation of wildlife response to recently disturbed habitat. In cases where disturbance results in a loss of usable habitat and subsequent animal avoidance, selection of annually aggregated disturbance data could result in a failure to recognize the full impact of habitat loss.

Our results indicated that both male and female bears may be avoiding same-year disturbances, though the trend is stronger for females. Forest harvests are well documented to be attractors to bears to do the availability of food (Nielsen et al. 2004a). However, the establishment of berries will take at least a year. The noise and activity of humans during the year of harvesting may well be a deterrent to bears. The behavioural response of male bears to disturbance age is clearest in summer, where selection of disturbances increased markedly with age of disturbance. It is common to see differences in male and female patterns of habitat selection (Bourbonnais et al. 2013). The summer availability of bears likely explains the seasonal variation and related research has found that the spatial-temporal pattern of habitat selection, in female grizzly bears, has the strongest signal in summer (Smulders et al. 2012). Although sample size was insufficient to assess the impacts of offspring status on female patterns of habitat selection, we expect selection of disturbance to vary with presence and age of offspring and differences between summer and autumn responses to disturbance age may be partly associated with offspring (Smulders et al. 2012).

It is possible that recent disturbances have insufficient over- and mid-storey vegetation for visual cover and must mature before providing beneficial food resources (Ndegwa and Murayama 2009). During summer, a large part of the bears' diet is comprised of forbs such as *Trifolium* and *Equisetum* spp. (Munro et al. 2006), both of which are more common in forest harvests than in mature forests (Nielsen et al. 2004b). However, immediately following forest disturbance, the abundance of forbs is likely reduced, and gradually increases for older disturbances before reaching a maximum abundance. In the case of locations subject to forest harvesting, subsequent successional developments mean that increasing age is positively correlated with increasing food availability (Nielsen et al. 2004c).

The consistently low selection of same-year disturbance, even when compared to one-year-old disturbance, suggests that the increased human activity associated with active forest disturbance may also discourage selection. Avoidance of human activity by grizzly bears is consistent with a recent study that found grizzly bears avoided habitat with active wellsites, but not habitat with inactive wellsites (Laberee et al. 2014). Given that 90 % of recorded grizzly bear deaths are found within 500 m of a road or 200 m of a trail (Benn and Herrero 2002), avoiding areas with human activity may reduce mortality (Nielsen et al. 2004b). The avoidance of young disturbances by grizzly bears may be a mechanism for avoiding human interaction (Graham et al. 2010). Although the food resources near roads provide important food for bears, the increased interaction with people leads to increased risk of mortality (Nielsen et al. 2004c; Benn and Herrero 2002).

16.7 Outlook

The integration of remote sensing and telemetry data is in its infancy and there are many future developments both in terms of the methods that need to be developed and the biological research questions that can be addressed. At present, improved approaches to integrating the disparate space-time scales of remote sensing and wildlife telemetry data are required. While wildlife habitat selection research often focuses on relatively large areas, unique insights are anticipated through the integration of high spatial resolution remote sensing data, sub-meter optical imagery and/or lidar, with high resolution telemetry data sets (e.g., Loarie et al. 2013). Rather than characterizing the interaction over large areas, examination of patterns between movement and habitat use in smaller exemplar areas may reveal trends that can then be scaled up using appropriate remotely sensed data products that represent habitat over large areas. Long time series remotely sensed data, especially that from the Landsat program, can provide informative baseline data as well as capture trends over time (White et al. 2011) that, in turn, can be integrated with telemetry data sets. There is also much potential to integrate remotely sensed data into movement research by developing approaches to interpolate, condition, and inform movement based on habitat conditions (Long and Nelson 2013).

While here we highlight the integration of telemetry and remotely sensed there is additional potential for these data types over a wide range of hypothesis generating and confirming research topics. For example, we can assess impacts of new roads on wildlife habitat selection, quantify how long after large machines leave an area it takes for wildlife to return, or to determine the influence of road closures on wildlife movement. Many of these research questions will benefit from data collection programs that have suitable overlap between telemetry data and landscape change.

16.8 Conclusions

An advantage when using disturbance products derived from remote sensing is the ability to synoptically and repeatedly map large areas. Using novel data processing to blend data with high temporal frequency with other imagery with fine spatial characterization provides for unique and otherwise unavailable data products. Through creating and applying data blending methods, such as offered by the STAARCH algorithm, high spatial and temporal resolution mapping of landscape change is afforded. These spatial tools may be most valuable for investigations covering large areas with needs for distance information within, as well as, between years. To act as an example of such an application, we demonstrated the use of high spatial and temporal resolution disturbance mapping products to provide a critical linkage disturbance and the GPS-based wildlife telemetry data. The new approaches and techniques presented here are useful in long-term monitoring efforts where it is important to determine species at risk population trends in conjunction with landscape change. However, probabilistic and model-based techniques must be developed and tested to enable differences in scale and limited overlap to be accounted for when investigating research questions. Research using low-temporal resolution disturbance data may generate results that misrepresent selection of disturbed habitat since same-year disturbances that occur before a GPS location is recorded are not differentiated from those occurring after the location is recorded. The preliminary findings of our case study suggest further investigation into the short term impacts of disturbance on habitat selection may be warranted. The complexity of interactions between bears, their habitat, and co-occurring disturbances is reiterated in our findings.

References

Asner GP (2013) Biological diversity mapping comes of age. Remote Sens 5:374–376. doi:10.3390/rs5010374

Benn B, Herrero S (2002) Grizzly bear mortality and human access in Banff and Yoho National Parks, 1971–98. Ursus 13:213–221

Berland A, Nelson TA, Stenhouse G, Graham K, Cranston J (2008) The impact of landscape disturbance on grizzly bear habitat use in the Foothills Model Forest, Alberta, Canada. For Ecol Manag 256:1875–1883

Bourbonnais ML, Nelson TA, Cattet MR, Darimont CT, Stenhouse GB (2013) Spatial analysis of factors influencing long-term stress in the grizzly bear (Ursus arctos) population of Alberta, Canada. PLoS One 8(12), e83768

Boyce MS, Pitt J, Northrup JM, Morehouse AT, Knopff KH, Cristescu B, Stenhouse GB (2010) Temporal autocorrelation functions for movement rates from global positioning system radiotelemetry data. Philos Trans R Soc B 365:2213–2219

Cohen WB, Goward SN (2004) Landsat's role in ecological applications of remote sensing. Bioscience 54:535–545

Cohen WB, Yang Z, Kennedy R (2010) Detecting trends in forest disturbance and recovery using yearly Landsat time series: 2. TimeSync Tools for calibration and validation. Remote Sens Environ 114:2911–2924

Gaulton R, Hilker T, Wulder MA, Coops NC, Stenhouse GB (2011) Characterizing stand replacing disturbance in western Alberta grizzly bear habitat, using a satellite-derived high temporal and spatial resolution change sequence. For Ecol Manag 261:865–877

Graham K, Boulanger J, Duval J, Stenhouse G (2010) Spatial and temporal use of roads by grizzly bears in west-central Alberta. Ursus 21:43–56

Gu Y, Wylie BK (2010) Detecting ecosystem performance anomalies for land management in the Upper Colorado River Basin using satellite observations, climate data, and ecosystem models. Remote Sens 2:1880–1891. doi:10.3390/rs2081880

He Y, Franklin SE, Guo X, Stenhouse GB (2009) Narrow-linear and small-area forest disturbance detection and mapping from high spatial resolution imagery. J Appl Remote Sens 3:033570

Healey SP, Cohen WB, Yang ZQ, Krankina ON (2005) Comparison of tasseled cap-based Landsat data structures for use in forest disturbance detection. Remote Sens Environ 97:301–310

Hebblewhite M, Haydon DT (2010) Distinguishing technology from biology: a critical review of the use of GPS telemetry data in ecology. Philos Trans R Soc B 365:2303–2312

Hilker T, Wulder MA, Coops NC, Linke J, McDermid G, Masek JG, Gao F, White JC (2009) A new data fusion model for high spatial- and temporal-resolution mapping of forest disturbance based on Landsat and MODIS. Remote Sens Environ 113:1613–1627

Huang C, Goward SN, Masek JG, Thomas N, Zhu Z, Vogelmann JE (2010) An automated approach for reconstructing recent forest disturbance history using dense Landsat time series stacks. Remote Sens Environ 114:183–198

Huete A, Didan K, Miura T, Rodriguez EP, Gao X, Ferreira LG (2002) Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sens Environ 83: 195–213

Johnson CJ, Heard DC, Parker KL (2002) Expectations and realities of GPS animal location collars: results of three years in the field. Wildl Biol 8:153–159

Justice CO, Vermote E, Townshend JRG, Defries R, Roy DP, Hall DK, Salomson VV, Privette JL, Riggs G, Strahler A, Lucht W, Myneni RB, Knyazkikhin S, Running SW, Nemani RR, Wan Z, Huete AR, van Leeuwen W, Wolfe RE, Giglio L, Muller J, Lewis P, Barnsley MJ (1998) The Moderate Resolution Imaging Spectroradiometer (MODIS): land remote sensing for global change research. IEEE Trans Geosci Remote Sens 36:1228–1249

Koehler GM, Maletzke BT, Von Kienast JA, Aubry KB, Wielgus RB, Naney RH (2007) Habitat fragmentation and the persistence of lynx populations in Washington State. J Wildl Manag 72:1518–1524

Laberee K, Nelson TA, Stewart BP, McKay T, Stenhouse GB (2014) Oil and gas infrastructure and the spatial pattern of grizzly bear habitat selection in Alberta, Canada. Can Geogr 8(1):79–94

Linke J, Mcdermid GJ, Laskin DN, Mclane AJ, Pape A, Cranston J, Hall-Beyer M, Franklin SE (2009) A disturbance-inventory framework for flexible and reliable landscape monitoring. Photogramm Eng Remote Sens 75:981–996

Loarie SR, Tambling CJ, Asner GP (2013) Lion hunting behaviour and vegetation structure in an African savanna. Anim Behav 85(5):899–906

Long JA, Nelson TA (2013) A review of quantitative methods for movement data. Int J Geogr Inf Sci 27(2):292–318

Masek JG, Huang C, Wolfe R, Cohen W, Hall F, Kutler J, Nelson P (2008) North American forest disturbance mapped from a decadal Landsat record. Remote Sens Environ 112:2914–2926

Mohr CO (1947) Table of equivalent populations of North America. Am Midl Nat 37:223–249

Munro RHM, Nielsen SE, Price MH, Stenhouse GB, Boyce MS (2006) Seasonal and diel patterns of grizzly bear diet and activity in west-central Alberta. J Mammal 87:1112–1121

Ndegwa MC, Murayama Y (2009) Analysis of land use/cover changes and animal population dynamics in a wildlife sanctuary in East Africa. Remote Sens 1:952–970

Nielsen SE, Boyce MS, Stenhouse GB (2004a) Grizzly bears and forestry I. Selection of clearcuts by grizzly bears in west-central Alberta, Canada. For Ecol Manag 199:51–65

Nielsen SE, Herrero S, Boyce MS, Mace RD, Benn B, Gibeau ML, Jevons S (2004b) Modelling the spatial distribution of human-caused grizzly bear mortalities in the Central Rockies Ecosystem of Canada. Biol Conserv 120:101–113

Nielsen SE, Munro RHM, Bainbridge EL, Stenhouse GB, Boyce MS (2004c) Grizzly bears and forestry II. Distribution of grizzly bear foods in clearcuts of west-central Alberta, Canada. For Ecol Manag 199:67–82

Nielsen SE, Stenhouse GB, Boyce MS (2006) A habitat-based framework for grizzly bear conservation in Alberta. Biol Conserv 130:217–229

Schneider RR (2002) Alternative futures: Alberta's boreal forest at the crossroads. The Federation of Alberta naturalists. Edmonton, Alberta

Schneider RR, Stelfox JB, Boutin S, Wasel S (2003) Managing the cumulative impacts of land uses in the Western Canadian Sedimentary Basin: a modeling approach. Conserv Ecol 7:8

Smulders M, Nelson TA, Jelinski DE, Nielsen SE, Stenhouse GB (2010) A spatially explicit method for evaluating accuracy of species distribution models. Divers Distrib 16:996–1008

Smulders M, Nelson TA, Jelinski DE, Nielsen SE, Stenhouse GB, Laberee K (2012) Quantifying spatial-temporal patterns in wildlife ranges using STAMP: a grizzly bear example. Appl Geogr 35:124–131

Stewart BP, Nelson TA, Laberee K, Nielsen SE, Wulder MA, Stenhouse GB (2013) Quantifying grizzly bear selection of natural and anthropogenic edges. J Wildlife Manag Wildlife Monographs 77:957–964. doi:10.1002/jwmg.535

Sunde P, Olesen CR, Madsen TL, Haugaard L (2009) Behavioural responses of GPS-collared female red deer *Cervus elaphus* to driven hunts. Wildl Biol 15:454–460

Vermote EF, Tanre D, Deuze JL, Herman M, Morcrette JJ (1997) Second simulation of the satellite signal in the solar spectrum, 6S: an overview. IEEE Trans Geosci Remote Sens 35:675–686

Wells AG, Wallin DO, Rice CG, Chang WY (2011) GPS bias correction and habitat selection by mountain goats. Remote Sens 3:435–459

White JC, Wulder MA, Gomez C, Stenhouse GB (2011) A history of habitat dynamics: characterizing 35 years of stand replacing disturbance. Can J Remote Sens 37:234–251

Woodcock CE, Allen R, Anderson M, Belward A, Bindschadler R, Cohen W, Gao F, Goward SN, Helder D, Helmer E, Nemani R, Oreopoulos L, Schott J, Thenkabail PS, Vermote EF, Vogelmann J, Wulder MA, Wynne R (2008) Free access to Landsat imagery. Science 320:1011

Wulder MA, Hall RJ, Coops NC, Franklin SE (2004) High spatial resolution remotely sensed data for ecosystem characterization. Bioscience 54:511–521

Wulder MA, White JC, Goward SN, Masek JG, Irons JR, Herold M, Cohen WB, Loveland TR, Woodcock CE (2008) Landsat continuity: issues and opportunities for land cover monitoring. Remote Sens Environ 112:955–969

Wulder MA, White JC, Masek JG, Dwyer J, Roy DP (2011) Continuity of Landsat observations: short term considerations. Remote Sens Environ 115:747–751

Wulder MA, Masek JG, Cohen WB, Loveland TR, Woodcock CE (2012) Opening the archive: how free data has enabled the science and monitoring promise of Landsat. Remote Sens Environ 122:2–10

Zhang X, Schaaf CB, Friedl MA, Strahler AH, Gao F, Hodges JCF (2002) MODIS tasseled cap transformation and its utility. In: Proceedings of the international geoscience remote sensing symposium 1063–1065 doi: 10.1109/IGARSS.2002.1025776