Multitemporal analysis of high spatial resolution imagery for disturbance monitoring

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Abstract

Mountain pine beetle red attack damage has been successfully detected and mapped using single-date high spatial resolution (< 4m) satellite multispectral data. Forest managers; however, need to monitor locations for changes in beetle populations over time. Specifically, counts of individual trees attacked in successive years provide an indication of beetle population growth and dynamics. Surveys are typically used to estimate the ratio of green (current) attack trees to red (previous) attack trees or G:R. In this study, we estimate average stand-level G:R, using a time series of QuickBird multispectral and panchromatic satellite data, combined with field data for three forested stands near Merritt, British Columbia, Canada. Using a ratio of QuickBird red to green wavelengths (Red-Green Index or RGI), the change in RGI (ΔRGI) in successive image pairs is used to estimate red attack damage in 2004, 2005, and 2006, with true positive accuracies ranging from 89 to 93%. To overcome issues associated with differing viewing geometry and illumination angles, which impair tracking of individual trees through time, segments are generated from the QuickBird multispectral data to identify small groups of trees. These segments then serve as the vehicle for monitoring changes in red attack damage over time. A local maxima filter is applied to the panchromatic data to estimate stem counts, thereby allowing an indication of the total stand population at risk of attack. By combining the red attack damage estimates with the local maxima stem counts, predictions are made of the number of attacked trees in a given year. Backcasting the current year's red attack damaged trees as the previous year's green attack facilitates the estimation of an average stand G:R. In this study area, these retrospective G:R values closely match those generated from field surveys. The results of this study indicate that a monitoring program using a time series of high spatial resolution remotely sensed data (multispectral and panchromatic) over select sample locations, could be used to estimate G:R over large areas, facilitating landscape level management strategies and/or providing a mechanism for assessing the efficacy of previously implemented strategies.

Introduction

The current outbreak of mountain pine beetle (*Dendroctonus ponderosae*) in western Canada is of unprecedented proportions; in 1999, the area impacted by mountain pine beetle was estimated to be 164,000 ha, and by 2006 the area impacted had increased to 9.2 million ha (Westfall, 2007). It is estimated that by 2013, 80% of the mature pine in British Columbia will have been killed by the beetle (Eng, 2005). The rapid expansion of the beetle population has been facilitated by the large amount of mature lodgepole pine, which has tripled in the last century as a result of intensive fire suppression activities (Taylor and Carroll, 2004). Several successive years of favorable climatic conditions have resulted in an increase in climatically suitable areas for brood development (Logan and Powell, 2004; Carroll et al. 2004; 2006a) and subsequent increases in mountain pine beetle range, northward, eastward, and to greater elevations.

Information Need

Counts of individual trees in consecutive years provide an indication of population growth and dynamics. Once a host tree has been attacked and killed by mountain pine beetle, its foliage will remain green for an initial period, and this is known as the green (current) attack stage (Wulder et al., 2006a). The foliage will gradually fade, and by 12 months after attack, 90% of killed trees will have red foliage (Amman, 1982; Henigman et al., 1999). This is the visually distinct red attack stage, and it is this stage of the infestation that may be captured by remote sensing methods (Wulder et al., 2006b). By three years after the initial attack, most of the killed trees will have lost all of their needles, and this is known as the grey attack stage (British Columbia Ministry of Forests, 1995). There is variability in the rate at which the foliage will discolor, depending on species and site conditions (Safranyik, 2004).

Given the magnitude and the spatial extent of the infestation in British Columbia, the information needs of forest managers are now focused on monitoring areas on the leading edge of the infestation, particularly areas along the border between the Canadian provinces of British Columbia and Alberta. Here, management efforts are attempting to reduce the spread of the mountain pine beetle further eastward into Alberta and beyond into the boreal forest. Typically, ground surveys are conducted annually to determine beetle population trends. The population trend of an infestation in a particular stand is determined by estimating the ratio of currently attacked trees (green attack) to one-year-old attacked trees (red attack) trees (G:R). This ratio is estimated from a sub-sample of trees in the stand (*i.e.*, based on randomly located transects). A ratio greater than 1 is indicative of an increasing population, while a ratio less than 1 is indicative of a declining population. The G:R is useful for estimating changes in the size of the beetle population and is one of the factors used to determine the management strategy for forest management units in British Columbia (e.g., suppression, salvage, monitoring) (British Columbia Ministry of Forests, 1995). Another form of survey is the over-wintering brood assessment survey, which is conducted in the spring by sampling under the bark of infested trees. These brood assessment surveys are used to estimate brood mortality and provide an indication of the rate of population increase (r-value) (Safranyik and Carroll, 2006).

High Spatial Resolution Remotely Sensed Data: Single Date Red Attack Mapping

High spatial resolution data provides the opportunity to track forest damage, such as that caused by mountain pine beetle, at a local scale. The level of detail and the flexibility for digital analyses afforded by high spatial resolution satellite data increases opportunities beyond what was previously possible with aerial photography and Landsat data (Sawaya et al. 2003). Single-date, high spatial resolution remotely sensed data have been used to map red attack damage at the forest stand and individual tree level. White et al. (2005) use a single date IKONOS 4 m multi-spectral data to detect mountain pine beetle red attack damage in forest stands with low and moderate levels of attack, and compared red attack damage estimates to estimates generated from air photo interpretation. Results indicate that within a one-pixel buffer (4 m) of identified damage pixels, the accuracy of red attack detection was 70.1% for areas of low infestation (stands with less than 5% of trees damaged) and 92.5% for areas of moderate infestation (stands with between 5% and 20% of trees damaged). Analysis of red attack trees that were missed in the classification of the IKONOS imagery indicate that detection of red attack was most effective for larger tree crowns (diameter >1.5 m) that were <11 m from other red attack trees.

Coops et al. (2006a) used helicopter GPS measurements of beetle infested pine trees in north-central British Columbia to identify areas of attack and non-attack stands on QuickBird 2.4 m multispectral data (blue, green, red, and near-infrared). Using a 50 m buffer around each GPS point, the authors tested the ANOVA separability of each of the spectral bands along with a greenness index and red/green spectral ratio under four classes: sunlit non-attacked crowns, dense red attack crowns, fader crowns, and shadowed crowns. Based on the results of the ANOVA, spectral thresholds were used to generate a binary map for red attack and non-attack (combining non-attacked crowns with crowns obscured by shadows). The results show that the ratio of the red to green QuickBird spectral bands was the most significant band combination for detecting red attack beetle damage, and the red attack identified with the QuickBird imagery had good correspondence to both forest health survey data and broader spatial resolution Landsat imagery. At the landscape scale, improvements in mountain pine beetle red attack detection and mapping have been facilitated by the use of multi-temporal Landsat imagery (Skakun et al., 2003; Coops et al., 2006b; Wulder et al., 2006c). The authors anticipated that a similar improvement in detection accuracy would be possible with multiple dates of high spatial resolution data.

Change Detection with High Spatial Resolution Imagery

Until recently, change detection using high spatial resolution imagery has been constrained to the use of aerial photographs. Since high spatial resolution satellite sensors have only been in commercial operation since 1999, the acquisition of satellite-based high spatial resolution images in a temporal sequence has been unavailable due to limited image archiving, difficulties in acquiring cloud-free imagery, and prohibitive costs. Other issues, such as viewing geometry and illumination conditions also complicate the use of high spatial resolution satellite imagery for change detection (depending on the desired target). QuickBird has a revisit rate of 3 to 7 days as a result of the sensor's variable cross-track and in-track viewing capability and while this offers temporal flexibility, the off-nadir viewing geometry confounds change detection approaches. Revisit rates for IKONOS are similar, with 3-5 days for off-nadir and 144 days for true-nadir imagery.

Im and Jensen (2005) concluded that traditional approaches to change detection fail to operate successfully with high spatial resolution data, primarily because of the proliferation of high frequency, high contrast objects (shadows) in these images, and the impact of off-nadir view angles that cause horizontal layover of vertical objects such as trees and buildings. This is especially true in forests, as object-oriented crown delineation using either high spatial resolution satellite imagery (Kasper and Phinn, 2006) or small-format aerial photography (Key et al., 2001) has been met with limited success with the exception in very high spatial resolution (<30cm) images (Pouliot et al., 2002). Asner and Warner (2003) examined the influence of varying viewing and illumination geometries on estimations of shadow fraction. They conclude that the variability in viewing and illumination geometries can have an impact on studies of vegetation structure; significant changes in scene reflectance characteristics can result solely from different observation geometry. Such effects are not limited to high spatial resolution data or to forest environments (Smith and Wise, 2007).

Approaches to change detection with remotely sensed data are typically based on visual interpretation (Clarke et al., 2004), pixel-based (Lambin and Strahler, 1994; Mas, 1999; Allen and Kupfer, 2001; Im and Jensen, 2005), or object-based methods (Desclée et al., 2006). Change detection methods often form an integral part of any monitoring system that incorporates remotely sensed data. Pixel-based change detection requires extremely accurate co-registration of images (Townshend et al., 1992), and often produces result that are heterogeneous or "salt and pepper" in appearance (Gong and Xu, 2003). This is caused by both random variation in the sensor's response, and intrinsic variability in the target (*e.g.*, forests). Object-based change detection approaches have emerged as a result of improved image segmentation capabilities (Möller et al., 2007). Image segmentation is the partitioning of a digital image into a set of jointly exhaustive, mutually disjoint regions that are more uniform within themselves than when compared to adjacent regions.

Liu et al. (2006) used Airborne Data Acquisition and Registration (ADAR) data (approximately 1 m spatial resolution) for monitoring the spread of Sudden Oak Death over a two year period in forest environment of coastal California. They implemented a pixel-based method of change detection by combining Support Vector Machines and Markov Random Fields model accounting. Challenges were encountered in image-to-image registration due to the wide view angle of the sensor (nadir ± 35°), variation in the terrain, low flying altitude and aircraft yaw, pitch, and roll. By incorporating spatial-temporal contextual information into the classification of Sudden Oak Death, the accuracy of the disease detection improved.

Desclée et al. (2005) implemented an object-based approach to forest land cover change detection using 3 SPOT-HRV images (20 m spatial resolution), collected over a 10 year period. The objective of this study was to automate the identification of change/no-change in a manner that was scene-independent. Their method incorporated image segmentation, image differencing, and stochastic analysis of multispectral data (OB-Reflectance method). The authors concluded that their multi-date segmentation approach effectively constrained variability for subsequent statistical analysis. Change was identified through spectral differencing, and the authors identified the primary advantages of the object based approach were cited as reduced processing time, less sensitivity to pixel registration errors, and no requirement for a predefined threshold to distinguish change segments from no-change segments. While the latter may be true if you are only interested in a binary change map, detail on a specific type of change would require a threshold and associated calibration data.

Objectives

The objective of this project was to establish a forest health monitoring system that would address the information need of forest managers concerning the spread of mountain pine beetles, such as eastward from British Columbia into Alberta and beyond. Specifically, the goal was to use high spatial resolution remotely sensed data to capture two critical pieces of information: first, tree based estimates of red attack damage; and secondly, an estimate of stem density. By combining these two pieces of information, the number of red attack trees could be estimated for any given year, and then by backcasting these estimates, retrospective G:R ratios could be generated. This method also gives an estimate of the population-at-risk (total stems), which is information not typically provided by ground surveys. The approach would allow G:R to be generated over large areas, providing a synoptic view of spatial variation in G:R which then in turn could be used for strategic planning of landscape level beetle management practices and/or to assess the efficacy of strategies and management practices implemented.

Study Site

The study site is located at Angstad Creek, 25 km south of Merritt, British Columbia, Canada, centered at approximately 49.84º N and 120.75º W (Figure 1). This site was originally selected for a study on mountain pine beetle outbreak development, designed to examine the transition from endemic to incipient endemic population levels (Carroll et al., 2006). Criteria for site selection included a historically suitable climate for mountain pine beetle (Carroll et al., 2004), and an absence of detectable beetle activity at the site, or within 10 km of the site, in 2002. From 2002 to 2005, regular field surveys were conducted in selected forest stands in the study area to monitor mountain pine beetle populations. Three of these stands (denoted as A, B, and C) were used in our analysis, ranging in size from 10 to 18 ha, containing pine as leading species, that were greater than 80 years of age, with moderately dense stocking (800 -1500 stems/ha)) (Carroll et al., 2006b). Variable prism plots in each of the stands indicated that the mensurational characteristics of the stands surveyed were sufficiently uniform (Table 1) and highly susceptible to mountain pine beetle attack (*i.e.*, lodgepole pine).

<Insert Figure 1 about here>
<Insert Table 1 about here>

Data

Remotely Sensed Data

Four QuickBird-2 images were acquired annually during the 2003 to 2006 summer growing seasons (Table 2 and Figure 2). The sun elevation at the time of image acquisition ranged from 53 to 58 degrees, and the off nadir view angles ranged from 7.7 to 14.6 degrees (Figure 3). QuickBird imagery contains four multispectral bands with a 2.5 m spatial resolution: 0.45-0.52 μm (blue); 0.52-0.60 μm (green); 0.63-0.69 μm (red); 0.76-0.90 μm (near infra-red); and a panchromatic band (0.45-0.90 μm), with a 0.68 m spatial resolution (Birk et al., 2003).

<Insert Table 2 about here>
<Insert Figure 2 about here>
<Insert Figure 3 about here>

Forest Health Survey Data

A baseline census of stands A, B, and C was completed in 2002; a survey grid was established in each stand, and the location of each tree referenced by a bearing to the nearest grid point. In this way, each tree became a survey point, and a stem map was generated for each stand. At four-week intervals between June and September of each year from 2002 to 2005, the health status of all trees in stands A and B were assessed and recorded; trees in stand C were surveyed and categorized for health status only once per year in mid-September (Carroll et al., 2006b). No field data was collected in Stand B after 2004, as at that point, the beetle populations in the stand had reached epidemic levels. In total, 906 trees surveyed between 2002 and 2005 were attacked by mountain pine beetle (176 in Stand A, 663 in stand B, and 67 in stand C).

Methods

Figure 4 outlines the methodology used to estimate G:R ratios for each of the stands. Each component of this schematic is described in detail in the following sections.

<Insert Figure 4 about here>

Image radiometric and geometric pre-processing

The QuickBird images were received as Standard Image products, in at-sensor radiance, from the data provider (DigitalGlobe Inc., 2007). All pre-processing on the panchromatic and multispectral bands were done independently. Multi-temporal analysis necessitates calibration of pixel values (Wu et al., 2005); radiance values were converted to top-of-atmosphere (TOA) reflectance using the gains and offsets provided in the image header files along with solar exoatmospheric irradiances estimated from normalized spectral response data (DigitalGlobe Inc., 2007) and a standard extraterrestrial solar spectrum reference (American Society for Testing and Materials, 2000).

The 2003 image was georeferenced to Terrain Resource Information Management II (TRIM II) (British Columbia Ministry of Environment Lands and Parks, 2005) aerial photography (1:20,000) using a third order polynomial and a cubic convolution resampling algorithm, resulting in a root-mean-square (RMS) error of 0.5 pixels (1.2 m). The 2003 image was then used as the control image to which the 2004, 2005, and 2006 images were subsequently coregistered (also using a third order polynomial and a cubic convolution resampling algorithm). For all three images, the final RMS error was less than 0.5 pixels (1.2m) for the multi-spectral bands, and less than 1 pixel (0.6m) for the panchromatic image band. A minimum of 15 GCPs were used for each of the geometric corrections.

Red attack detection

Locations of red attack damage were identified by calculating and thresholding the ΔRGI values for each image pair (2003-2004; 2004-2005; 2005-2006). For this study, field survey data were used to determine which trees experienced attack by mountain pine beetle, with the crowns gradually turning red (and detectable with remotely sensed data) in the following year. Therefore, trees identified in the survey as having been attacked in 2003, would have turned the characteristic red color in 2004, while crowns of trees attacked in 2004 would appear red in the 2005 image (and so on).

For each image, a ratio of the red to green wavelengths was computed (hereafter referred to as the Red-Green Index or RGI). This index emphasizes the spectral change in foliage color from green to red, and has been used successfully for detecting mountain pine beetle red attack damage with single-date QuickBird imagery (Coops et al., 2006a). Using a multi-date approach for change detection, the RGI values from the 2004 image were subtracted from the corresponding RGI values from the 2003 image, and the change in RGI values was calculated (hereafter referred to as ΔRGI_2004).

A 10% sub-sample (n = 90) of the field data was selected at random for calibration purposes, with the remainder of the field data used for validation. For example, a subset of the 2003 forest health survey was used to iteratively determine the upper and lower limit of ΔRGI_2004 values that corresponded to red attack damage (as differences in RGI values spanned a range of conditions, including harvesting). The sub-sample of the field data was used to assess the omission and commission error resulting from the threshold, with the objective being to adjust the threshold to minimize these errors. The final threshold was then applied to the ΔRGI_2004 values to create a data layer identifying red attack damage in stands A, B, and C in 2004. A similar process was then used to identify red attack damage that manifested in 2005 (ΔRGI_2005) and 2006 (ΔRGI_2006). This processing provided locations of red attack damage in stands A, B, and C, in 2004, 2005, and 2006. Accuracy of the red attack detection was assessed at the segment level using field data. Agreement occurred when a segment contained red attack identified by thresholding the ΔRGI and attack measured in the field.

Image segmentation

The different viewing geometry and illumination conditions, combined with the potential for error in co-registering multiple years of imagery with ancillary ground surveys (Weber et al. 2007), posed challenges for tracking the health status of individual trees through time. As a result, an alternative approach was developed that tracked groups of trees (or pixels) through time. This was achieved by segmenting the 2003 QuickBird multispectral image. Segments were generated using all four multispectral bands in eCognition software (Definiens GmbH, München, Germany) with the following parameters: equal weights for all bands; scale = 15; shape = 0.9; color = 0.1; compactness = 1; smoothness = 0). For the three stands of interest, the average size of the segments ranged from 347 to 405 m^2. Stand A had 454 segments; stand B, 596 segments; and stand C, 313 segments.

Estimating stem counts

Recall that the information need associated with monitoring mountain pine beetle attack at the tree level is the ratio of the number of trees in the green attack stage, to the number of trees in the red attack stage. In order to fulfill this information need, some approximation of the number of trees in each stand was required. A local maxima filter (Wulder et al. 2000) was applied to the panchromatic QuickBird image for each year to identify individual tree crowns. Past research has indicated that local maxima filtering is biased towards larger tree crowns (Wulder et al., 2000; Wulder et al., 2004b), which is not a concern for this application for two reasons: first, the information need requires a relative estimate of green attack to red attack trees (and changes to that ratio over time) – not an exact census of all trees in the stand; secondly, since larger tree crowns are typically associated with larger, mature trees, and it is these larger trees that are most susceptible to attack by mountain pine beetle (Shore and Safranyik, 1992), the omission error for individual crowns is considered acceptable. The advantage of this approach over other methods is that it provides an indication of the population-at-risk of attack by mountain pine beetle. A local maxima filter was applied to each QB PAN image and the impact of different viewing geometry and illumination conditions on tree counts were assessed using Analysis of Variance (ANOVA) on tree counts by segment.

Estimating G:R

Figure 4 summarizes how the remotely sensed outputs of red attack damage, image segments, and estimates of stem count were combined to estimate the G:R ratio. First, the remotely sensed output (calculated from ΔRGI) is used to determine the area of red attack damage found within the segment. The proportion of red attack area relative to total segment area is then calculated, and that proportion is then applied to the segment stem count (calculated from applying the local maxima filter), resulting in an estimate of the number of trees attacked in the segment for a given year. For example, if ΔRGI indicates that 25% of a segment is red attack in 2004 and the segment has 100 trees, then 25 trees are assumed to be red attack in the segment in 2004. The red attack trees in any given year are assumed to have been green attack in the previous year; hence, red attack trees in 2005 are assumed to have been green attack in 2004. Using this approach, we are able to retrospectively construct a G:R ratio for a given year, as well as estimate a rate of population increase for multiple years (Figure 5). G:R ratios were not calculated for all segments in the stand, rather, segments were stratified based on their health status as determined using ΔRGI (only segments with attack were used). From these a random sample of attacked segments representing approximately 15% of the stand area was used in calculating the G:R ratios; the stand G:R ratios are the average of the G:R in each of the randomly selected segments within each stand.

<Insert Figure 5 about here>

Results

Red attack detection

Red attack damage identified from the QuickBird imagery was compared to locations of red attack damage recorded by field survey. Agreement between the field survey and the remotely sensed outputs occurred when a segment contained a ground survey point (tree) identified as red attack (2002-2005), and also contained red attack in the remote sensing outputs (2004-2006). The results of the accuracy assessment are summarized in Table 3 and indicate a strong correspondence between the field survey and the remotely sensed change mapping, with true positive accuracies ranging from 89 (stands A and C) to 93% (stand B).

<Insert Table 3 about here>

Estimation of stem counts

As discussed earlier, varying viewing geometry and illumination conditions (Table 2), combined with complex forest structure, result in variability in the number and position of local maxima from one image to the next. This shift in a tree's position over time precludes monitoring of individual trees through time (using data of this spatial resolution, with these collection parameters). However, if the image is segmented based on its spectral properties, the resulting segments, representing small groups of trees, could be monitored through time and account for this variability in positional accuracy. For monitoring purposes, it is desirable to identify the population-at-risk in the first year of the study (e.g., through a baseline census). For monitoring red attack damage, a local maxima filter would ideally be applied to the first year of imagery to provide an estimate of stem count per segment, with the assumption that the stem count would remain constant over time (depending on the time horizon for monitoring; a long-term study, > 5-10 years would likely have to account for tree regeneration and mortality). To verify this assumption that stem counts per segment would not vary significantly through time, we applied a local maxima filter to each year of imagery and generated a stem count from each year. An ANOVA on the tree counts, by segment, found that tree counts did not vary significantly from one year to the next (Table 4). As a result, we used the local maxima output from the 2003 image to represent individual stem counts within each segment. The average stem count per segment in stands A, B, and C in 2003 was 22, 18, and 20, respectively.

<Insert Table 4 about here>

Estimation of G:R

Table 5 includes the estimated G:R for each stand in 2004 and 2005. The stand G:R is the average of the G:R for each of the sampled segments within each stand (with sample sizes for each stand indicated in Table 5). For stands A and B, the G:R is very similar to the G:R derived from the field survey. In Stand B, the remotely sensed estimate of G:R is greater than the field surveyed G:R in 2004, and remains constant in 2005. Unfortunately, no field data were collected in stand B in 2004 and so no comparable field based G:R is available for 2005. Based on 2003 field survey however, we know that the G:R was 4 in

2003 – indicating that the population in this stand has been steadily increasing in past years (Carroll et al., 2006b).

Figure 6 provides an example of segment 42414 in stand B. This segment had an area of 0.14 ha and contains approximately 73 trees (as estimated by the LM filter approach). ΔRGI_2004 indicated that 1% of the segment, or 1 tree had red attack damage in 2004. By 2005, the mountain pine beetle population in stand B had increased dramatically and ΔRGI_2005 indicated that 33% of the segment area, or approximately 24 new trees had red attack damage. The G:R for 2004 was therefore 24:1. This level of increase is extreme and theoretically improbable – emphasizing the need to estimate the average G:R over a larger spatial unit (British Columbia Ministry of Forests, 1995). In 2006, the rate of red attack expansion decreased from 2005, with 11% of the stand or 8 additional trees having red attack damage.

<Insert Figure 6 about here>

Discussion

The different viewing geometry and illumination conditions for each of the images used in this study, as illustrated in Figure 3 and 6, confounded efforts to track individual trees through time; images in 2003 and 2004 were acquired with fairly similar parameters, whereas the 2005 image has a very different solar azimuth and in-track view angle (Table 2). For the establishment of a monitoring system intended to cover large areas, differences in viewing and illumination geometry is an issue, not only temporally but also spatially. Furthermore, the cost of acquiring high spatial resolution data over large areas can be prohibitive, and increases overhead with the processing requirements of multiple scenes over a large area. The authors therefore recommend that the approach presented in this paper be implemented through a sampling protocol, whereby an area of interest is stratified using data appropriate for identifying areas with a high likelihood of beetle attack (*e.g.,* leading species, age, elevation, Landsat red attack maps, and etcetera). Satellite sample plots could then be established (8km by 8km), and QuickBird or some other high spatial resolution data source acquired over these areas. Further, it should be stressed, as is evident in Figure 5, that the geometric match between scenes is good, it is the interaction of the sun / surface / sensor geometry with the forest structural conditions that results in the unique manifestation of the forest and the subsequent image processing and tree-to-tree matching difficulties (Wulder et al., 2004a).

For local scale characterization with high spatial resolution data, high levels of precision are required to accurately co-register images (Stow, 1999) and similarly, to co-register image outputs with field surveys (Weber, 2006; Weber et al., 2007). Others have suggested taking imagery into the field to ensure survey data and remotely sensed data are properly aligned as the data is collected (Sawaya et al., 2003). Unfortunately, field and image data are not often collected in this manner, with field data sometimes originating from a different project (and therefore collected at a different time, with different objectives). Therein lies the appeal of object based approaches; generalization to a smaller (and often meaningful) spatial unit allows positional ambiguity to be accounted for. In the case of high spatial resolution data, these segments often represent individual trees or small groups of trees. In the case of mountain pine beetle, the timing of data collection is particularly problematic, due to the specific bio-window within which survey data can be collected (Wulder et al. 2006b).

It must also be reiterated that there are data sources and procedures that are used operationally to address the G:R information need. Coarse level aerial overview surveys are conducted province-wide on an annual basis. The locations of damage identified from these surveys are then used to direct more detailed aerial surveys, which in turn are used to direct the location of ground surveys, such as those used to generate estimates of G:R. Furthermore, these estimates can often be generated relatively quickly, whereas the approach presented herein is primarily retrospective, since it requires at least three dates of imagery to estimate G:R. This approach does however provide unique benefits for areas where, for whatever reason, there was a temporal gap in data collection, field crews are unable to access the site, or there is a need to assess the efficacy of previously implemented management practices. Also – this approach is a consistent and repeatable method for generating G:R over larger areas, where economies of scale would make this approach more affordable than the deployment of field crews. The authors are not proposing that this data would supplant other sources, but rather could supplement and augment these other pieces of information.

While it was possible to successfully acquire multi-year high spatial resolution data for this study area, there are risks associated with the assumption that quality imagery will be available for the specific bio-window desired. Commercially available high resolution satellite data is not routinely archived, so sensors must be tasked to acquire data over area of interest. As demand for this data increases, it becomes increasingly difficult to get data when and where it is required. Typically, an image order must be put in months in advance. Particular requests may be made to limit viewing angles, solar conditions (collection date range), cloud cover, mosaicking of multiple over-passes, etcetera. While these types of parameters may be customized, any limitations to the conditions under which an image may be collected decreases the likelihood that imagery will be successfully obtained.

Conclusion

In this paper we presented an approach for estimating rates of mountain pine beetle population change, via G:R, with high spatial resolution remotely sensed data. The average G:R is an important source of information for forest managers who need to monitor changes in beetle populations over time. Using both the multispectral and panchromatic bands from multiple dates of QuickBird data, we were able to characterize red attack damage and estimate stem counts. By combining these two pieces of information, the number of red attack trees could be estimated for any given year, and then by backcasting these estimates, G:R ratios could be generated retrospectively. This method also gives an estimate of the population-at-risk (total stems), something that is typically not collected when conducting ground surveys. The challenges and risks associated with using high spatial resolution remotely sensed data to monitor forest damage over time have also been enumerated. The approach presented would allow G:R to be generated over large areas, providing a synoptic view of spatial variation in G:R which then in turn could be used for strategic planning of landscape level beetle management practices and/or to assess the efficacy of strategies and management practices implemented.

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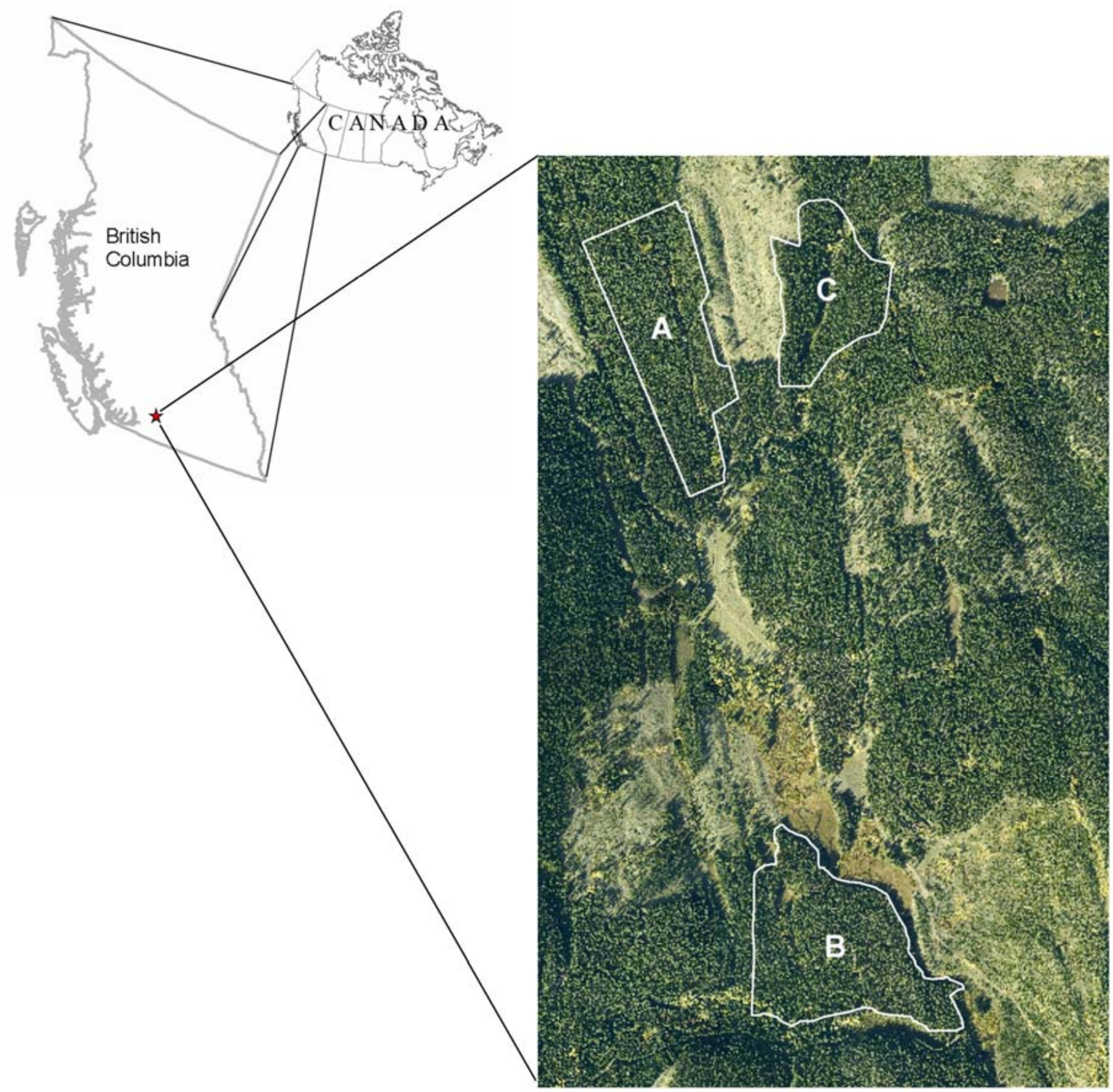


Figure 1

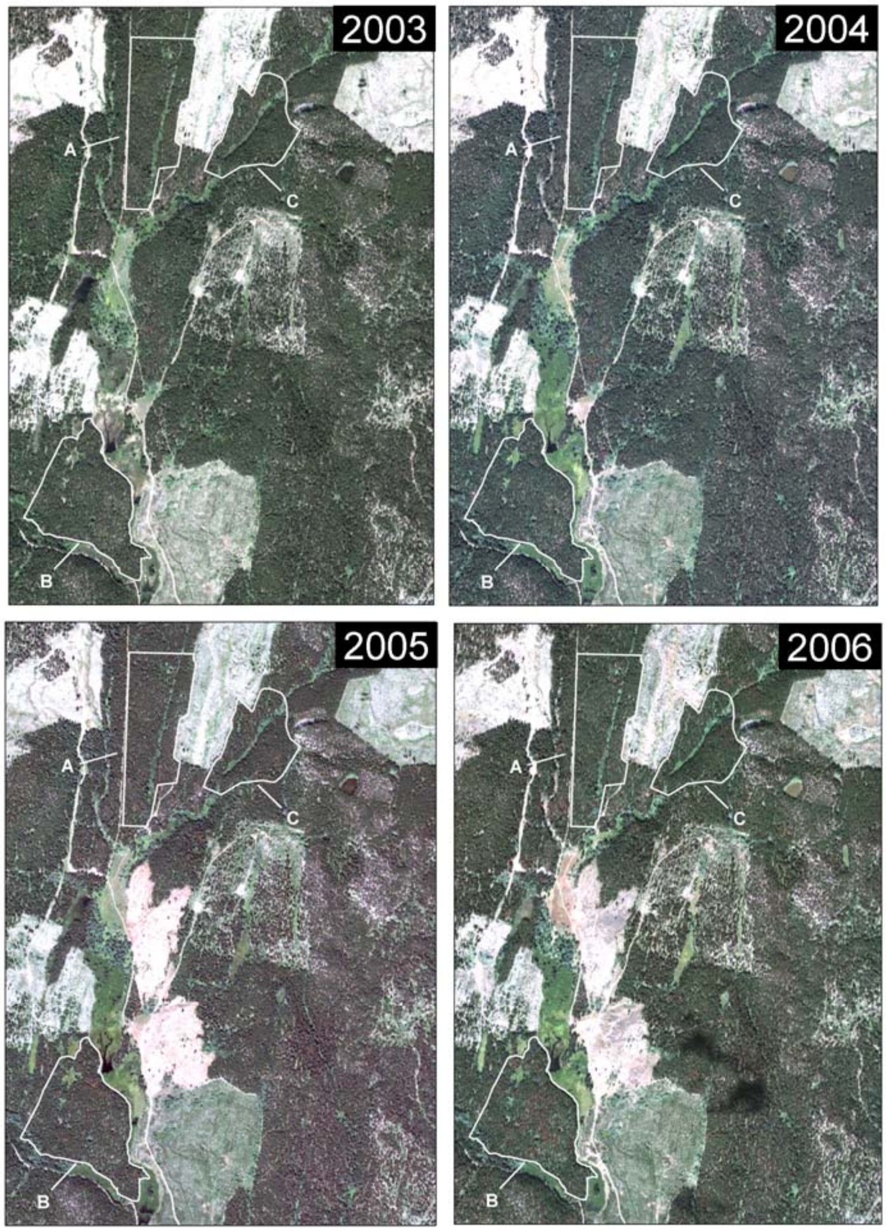
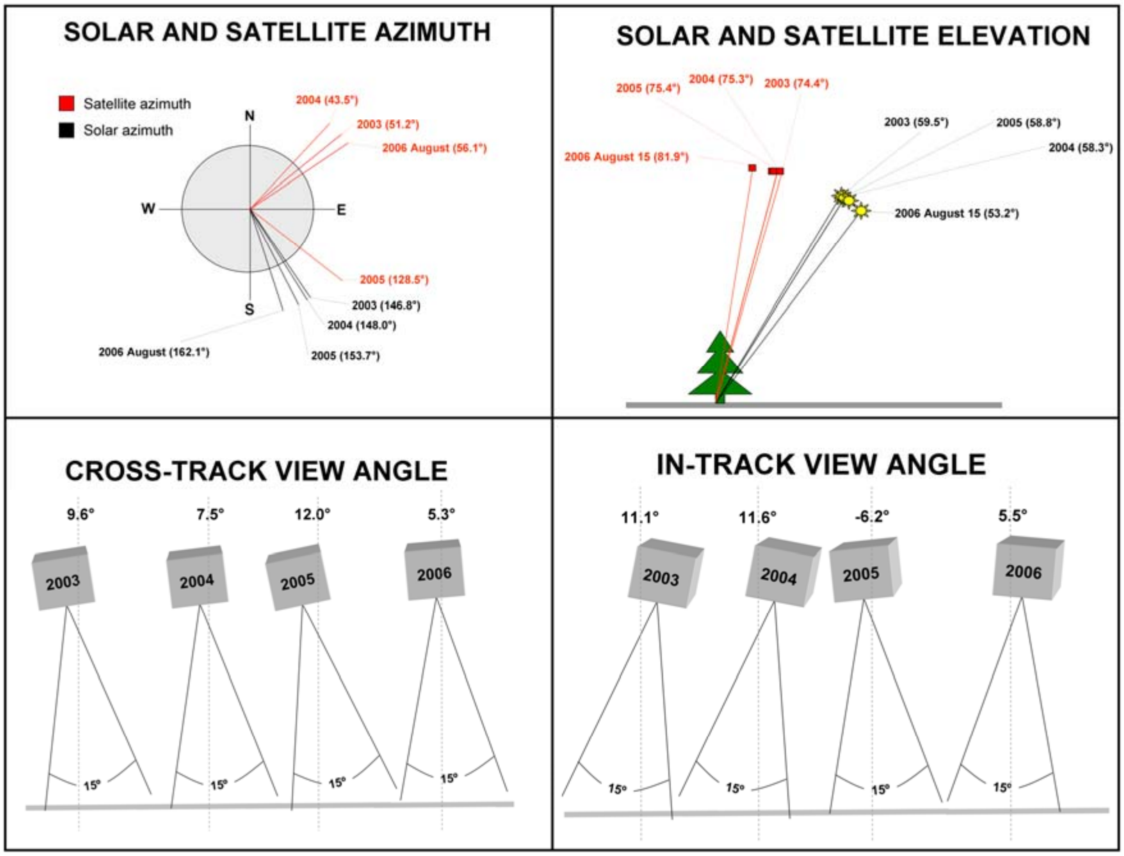


Figure 2



SOLAR AND SATELLITE AZIMUTH
Satellite azimuth
Solar azimuth
N
W
E
S
2004 (43.5°)
2003 (51.2°)
2006 August (56.1°)
2005 (128.5°)
2003 (146.8°)
2004 (148.0°)
2006 August (162.1°)
2005 (153.7°)
SOLAR AND SATELLITE ELEVATION
2005 (75.4°)
2004 (75.3°)
2003 (74.4°)
2006 August 15 (81.9°)
2003 (59.5°)
2005 (58.8°)
2004 (58.3°)
2006 August 15 (53.2°)
CROSS-TRACK VIEW ANGLE
9.6°
7.5°
12.0°
5.3°
2003
2004
2005
2006
15°
IN-TRACK VIEW ANGLE
11.1°
11.6°
-6.2°
5.5°
2003
2004
2005
2006
15°

Figure 3

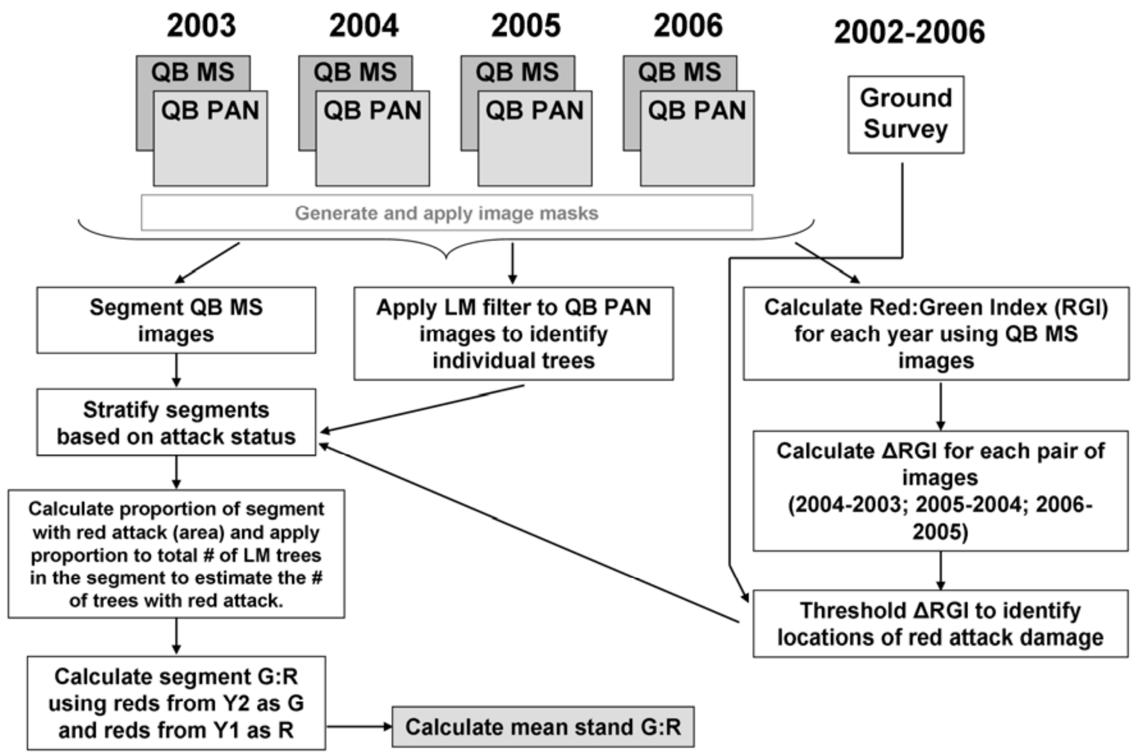
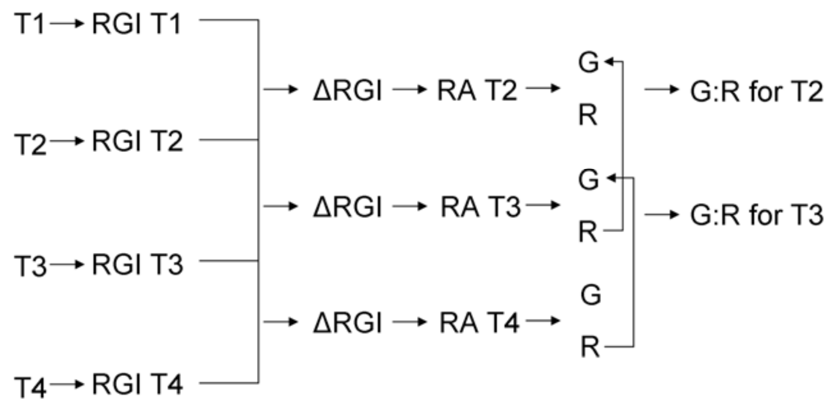

2003
2004
2005
2006
2002-2006
QB MS
QB PAN
Ground Survey
Generate and apply image masks
Segment QB MS images
Apply LM filter to QB PAN images to identify individual trees
Calculate Red:Green Index (RGI) for each year using QB MS images
Stratify segments based on attack status
Calculate ΔRGI for each pair of images (2004-2003; 2005-2004; 2006-2005)
Calculate proportion of segment with red attack (area) and apply proportion to total # of LM trees in the segment to estimate the # of trees with red attack.
Threshold ΔRGI to identify locations of red attack damage
Calculate segment G:R using reds from Y2 as G and reds from Y1 as R
Calculate mean stand G:R

Figure 4



Where:

T1…T4 = year of image acquisition

RGI = Red Green Index (spectral index calculated using red and green bands from QB multispectral data).

ΔRGI = Change in RGI calculated by subtracting the RGI for one year from the RGI for the following year.

RA T2 = red attack in T2

To calculate the G:R ratio for any given year, the red attack from the following year is used as green attack for the previous years calculation.

Four dates of imagery will give red attack estimates for three years and G:R for two years.

Figure 5

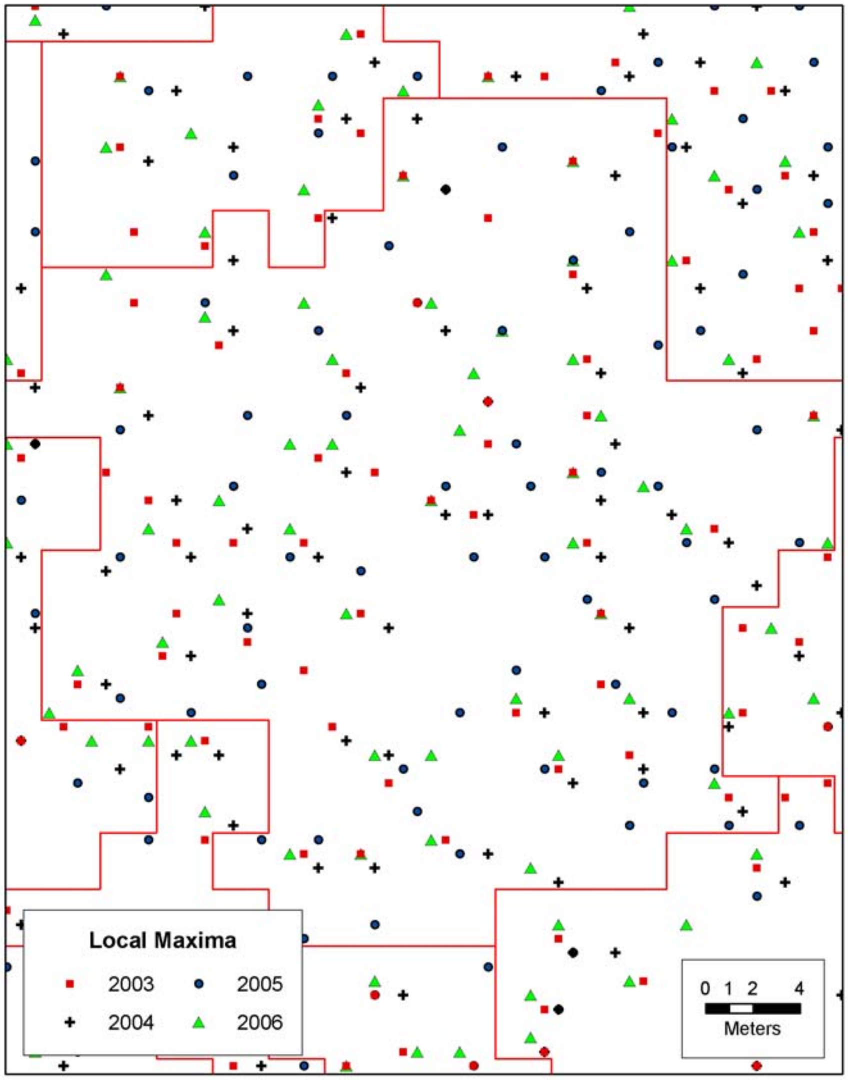


Figure 6

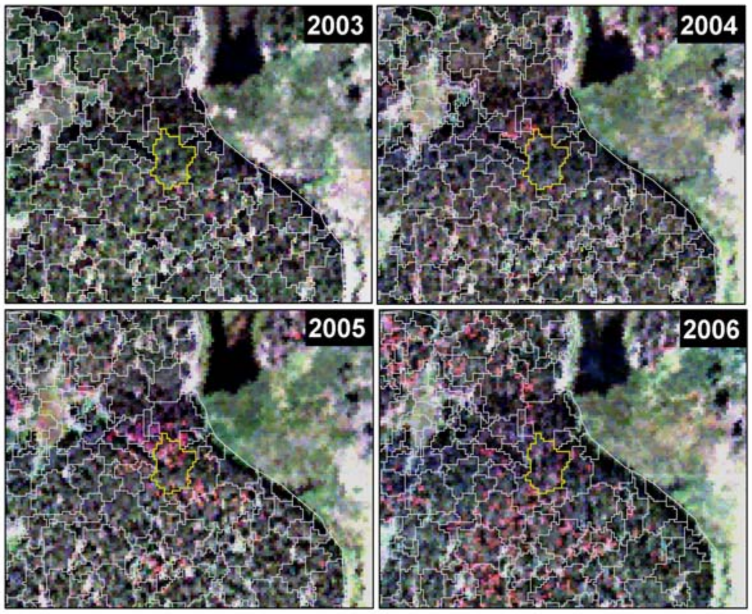


Figure 7

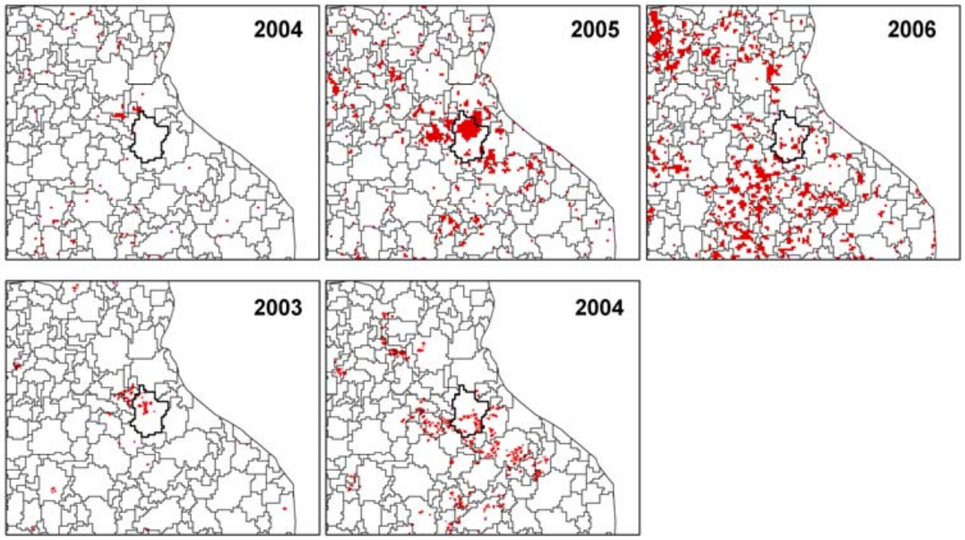


Figure 8