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Improvement of Low Level Bark Beetle Damage Estimates with Adaptive Cluster Sampling

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Detection of low level infestation in forest stands is of principle importance to determine effective control strategies before the attack spread to large areas. Of particular concern is the ongoing mountain pine beetle, *Dendroctonus ponderosae* (Hopkins) epidemic, which has caused approximately 14 million hectares of damage to lodgepole pine (*Pinus contorta* Dougl. ex. Loud var. *latifolia* Engl.) forests in western Canada. At the stand level attacked trees are often difficult to locate and can remain undetected until the infestation has become established beyond a small number of trees. As such, methods are required to detect and characterise low levels of attack prior to infestation expansion, to inform management, and to aid mitigation activities. In this paper, an adaptive cluster sampling approach was applied to very fine-scale (20 cm) digital aerial imagery to locate mountain pine beetle damaged trees at the leading edge of the current infestation. Results indicated a mean number of 7.36 infested trees per hectare with a variance of 18.34. In contrast a non-adaptive approach estimated the mean number of infested trees in the same area to be 61.56 infested trees per hectare with a variance of 41.43. Using a relative efficiency estimator the adaptive cluster sampling approach was found to be over two times more efficient when compared to the non-adaptive approach.

Keywords object-based classification, high spatial resolution, satellite, digital aerial imagery, mountain pine beetle, forest inventory, adaptive cluster sampling
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1 Introduction

1.1 Mountain Pine Beetle

Infestation by the mountain pine beetle, *Dendroctonus ponderosae* (Hopkins) is of particular importance in western Canada due to the widespread damage to pine forests and continues to be the leading cause of mortality across the region (Westfall and Ebata 2008). Infestations typically initiate in individual trees or small groups on the landscape that expand rapidly to large areas. In 1999, attack was estimated to cover an area of 164 000 hectares (Westfall and Ebata 2008), and by 2008 this area increased to over 13 million hectares (Westfall and Ebata 2009). In British Columbia, beetles have attacked the lodgepole pine (*Pinus contorta* Dougl. ex. Loud var. *latifolia* Engl.) forests that dominate much of the southern and central interior region of the Province. Infestation has continued to spread east into the pine forests of Alberta, some of which historically have been unaffected by the mountain pine beetle. In Alberta, the beetles have the potential to transition from lodgepole pine to jack pine (*Pinus banksiana* Lamb.) and infest the boreal forest should annual temperatures remain favourable for colonisation, emergence, and dispersal (Logan and Powell 2001, 2003, Carroll et al. 2004, 2006).

Expansion has occurred because previous limitations to infestation have relaxed, allowing large populations of mountain pine beetles to affect areas with no historical record of attack. Infestation has spread rapidly due to two factors, the first being favourable periods of weather sustained over long periods of time (Safranyik 1978) and more recently, alterations in climatic thresholds (Raffa et al. 2008) that historically caused mortality of beetles (minimum temperatures less than –40 °C) which have enabled larvae to survive cold winters, therefore increasing the size of the attacking population. Secondly, the abundant pine forests in the interior forests of British Columbia and western Alberta provide large areas of highly suitable host material for attack by the beetles (Safranyik 1978, Taylor and Carroll 2004).

1.2 Forest Health Monitoring

In western Canada, forest health surveys locate trees attacked by forest pests and monitor the spread of diseases and insect damage, and provide information to guide mitigation activities. Typically, control of infestations is implemented by detecting mountain pine beetle killed trees. Approximately one year after attack trees exhibit red foliage (known as red attack) which indicates the locations of infestation. Ground crews are dispatched to these locations and the infested trees in close proximity to the red attacks are located, felled, and burned (Maclauchlan and Brooks 1998). By removing infested trees the beetle population is decreased and future infestations will decline or remain stable because the number of attacking beetles available the following year is reduced. Given the nature of mountain pine beetle infestations to infest trees close to previously attacked trees it is possible that trees missed during surveys will be detected on the ground and the potential for future infestation expansion is further reduced (Carroll et al. 2006, Coggins et al. 2008).

Surveys record the cause of the damage, and assess the severity and extent of mortality within forest stands (Westfall and Ebata 2008). Mountain pine beetle attack information is collected using a variety of survey techniques, ranging from coarse (regional) to fine-scale (operational), with each used differently depending on the survey scale and the requirements of the end-user (Wulder et al. 2006a). Aerial overview surveys provide regional data and are completed by flying over the Province in fixed-wing aircraft to identify forest stands affected by pests and diseases, this regional information then guides finer-scale surveys over select portions of the land-base which record the damaging agent, number, and geographic location of infested trees.

Digital remotely sensed data can also be used to identify areas of forest pest and disease (Ciesla 2000). Historically, Landsat imagery (30-m spatial resolution) has been used to identify mountain pine beetle infestations, with detection accuracies ranging between 70% and 85% (Franklin et al. 2003, Skakun et al. 2003, Wulder et al. 2006b). Franklin et al. (2003) identified infestations within a 2-ha area on a single image acquired from the

TM sensor at an overall red attack detection accuracy of 73.3% ± 6%, $p = 0.05$ (Franklin et al. 2003). Skakun et al. (2003) processed a time series of Landsat TM data to identify and confirm red attack damage in forest stands. This approach produced an accuracy of 76% (± 12%, $p < 0.05$) for groups of 10 to 29 infested trees, and 81% (± 11% for groups of 20 to 50 infested trees). Multi-date Landsat scenes were also utilised by Wulder et al. (2006c) to monitor forest change due to mountain pine beetle infestation and reports an 86% accuracy (± 7%). High spatial resolution imagery has also shown ability to detect infestations. White et al. (2005) utilised IKONOS imagery (4-m multispectral spatial resolution) with an unsupervised clustering approach to identify infestations near Prince George, British Columbia. Light infestations (1% to 5% of the trees infested within a forest stand) were detected with an accuracy of 71% and moderate infestations (> 5% to < 20% of a forest stand) with 92.5%. Coops et al. (2006) used imagery from the QuickBird satellite (2.44 m multispectral spatial resolution) to detect red attack damage. The imagery was classified into attacked trees and healthy trees and the number of red pixels counted. The relationship between the number of red attack pixels and red attack crowns observed in forest health surveys was found to be significant ($r^2 = 0.48$, $p < 0.001$, standard error = 2.8 crowns). Very high spatial resolution digital aerial imagery (as fine as 5 cm) also has the potential to identify mountain pine beetle attack. Imagery is usually acquired in the visible portion of the electromagnetic spectrum (e.g. blue, green, red, approximately 0.4–0.7 μm) and has similar characteristics to aerial photographs. Coggins et al. (2008) utilised 10-cm spatial resolution digital aerial imagery to extract information including mountain pine beetle red attack, which was defined with an accuracy of 80.2% when compared to field plots.

1.3 Role for Sampling

A limitation of high spatial resolution satellite and digital aerial imagery is the small image extent, causing large area acquisition to be costly and resulting in the need for much image processing prior to analysis. The limited extent of very high spatial resolution airborne imagery is however, well suited to a sampling approach where imagery can be acquired over several smaller areas and integrated into a sampling scheme, from which forest health variables can then be defined. This technique offers a lower-cost solution to obtain accurate data over large areas in a statistically sound manner. Sampling for infestation in its simplest form can consist of conducting a simple random sample on a remotely sensed image with observations recorded in sample plots selected at random locations over the entire area of the image. Estimates of the mean, variance, and confidence limits for the number of red attacked trees are determined using simple random sample estimates. This method however, can provide high variability and a wide confidence range. Adaptive cluster sampling has been demonstrated to determine rare and elusive populations that are spatially clustered (Thompson 1990) and can provide estimates of population densities over large areas. Previous studies have utilised adaptive cluster sampling for a variety of applications including for example, providing estimates of low density mussel populations (Smith et al. 2003), estimating the density of wintering waterfowl (Smith et al. 1995), and estimating stock size of fish in estuarine rivers (Conners and Schwager 2002). In a forestry context this adaptive cluster sampling approach has also been utilised to assess the presence of rare tree species in Nepal (Acharaya et al. 2000), in combination with probability proportional to size sampling to predict forest inventory variables in the United States (Roesch 1993), and to inventory sparse forest populations in Finland (Talvitie et al. 2006).

1.4 Objectives

The goal of this paper is to demonstrate an approach for using samples of airborne imagery to produce robust estimates of population wide estimates of low level mountain pine beetle attack. To meet this goal, the primary objective is to determine the location and number of individual red attack trees within large areas by utilising an adaptive cluster sampling approach in a line transect design. To define areas of infestation an automated object-based classification system

(Bunting and Lucas 2006) was employed, and sites located along the transect lines. The mean number of infested trees and the variance was then calculated and compared to estimates of statistics derived from a conventional non-adaptive approach. A relative efficiency estimator was used to demonstrate the utility of the adaptive cluster approach to determine the number of mountain pine beetle killed trees over the landscape.

2 Materials and Methods

2.1 Site Description

This research was conducted in forests situated on the western slopes of the Canadian Rocky Mountains near the town of Tumbler Ridge, British Columbia, Canada (54°38´N, 120°41´W) (Fig. 1). This location is representative of economically valuable forest stands on the border between British Columbia and Alberta. The topography around the study area consists of high-elevation (1800 m) mountainous regions, mid-elevation forests (1200 m), and some low-elevation prairie land (900 m). The forests are dominated by mature lodgepole pine occasionally mixed with black spruce (*Picea mariana* (Mill.) BSP) which grow on valley sides. Sub-alpine fir (*Abies lasiocarpa* (Hook.) Nutt), western larch (*Larix occidentalis* Nutt.), and black spruce grow in flat areas, around swamps and on river banks.

Typically in this area, lodgepole pine naturally regenerates after fire which has resulted in even-aged, pine dominated, stands that grow to uniform dimensions (Moir 1965). The lodgepole pine present in the area are considered to be susceptible to mountain pine beetles due its proximity to the infestation spreading north and east across British Columbia and due to trees being larger than 12.5 cm. When combined with elevation and stand age these conditions are favourable to continue spread of the infestation (Shore and Safranyik 1992, Shore et al. 2000).

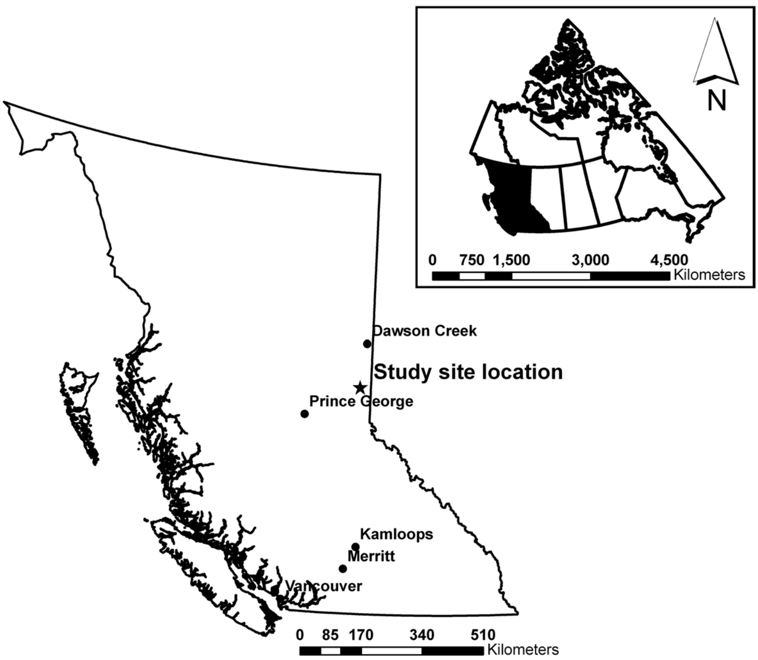

Fig. 1. The study area, situated near the town of Tumbler Ridge. The 20-cm spatial resolution digital aerial image is provided also to give context to the size of the sample area.

2.2 Data

2.2.1 High-Spatial Resolution Digital Aerial Imagery

High-spatial resolution digital aerial images were acquired with a Canon EOS-1Ds Mark II camera, with a f1.8 Canon lens fitted with a Bayer pattern filter, mounted on a fixed wing aircraft. The camera uses a complementary metal–oxide–semiconductor (CMOS) sensor which provides an effective resolution of 16.7 megapixels. Imagery was acquired during August 2007 from an altitude of 2200 m with a focal length of 85 mm to produce a spatial resolution of 20 cm. Illumination variation was reduced over each scene by acquiring imagery as close to solar noon as possible. Imagery was georectified to a QuickBird multispectral (2.44-m spatial resolution) image projected to UTM North American Datum 83. Image coordinates were supplied by an onboard GPS coupled with an inertial navigation system to assist accurate georectification. Imagery was acquired over an area of 40 km^2 (10 km × 4 km or 50 000 × 20 000 pixels) and mosaicked together to form a continuous image. Imagery was recorded in 3 channels representing the spectral ranges which approximate to: 0.4–0.5 μm (blue), 0.5–0.6 μm (green), and 0.6–0.7 μm (red).

2.3 Phase 1: Individual Tree Crown Delineation on 20 cm

Individual tree crowns can be delineated on high-spatial resolution imagery using object-based classification techniques and can be further classified according to species or health status. Bunting and Lucas (2006) successfully utilised Compact Airborne Spectrographic Imager remotely sensed data to define individual tree crowns in Australian forests with accuracies of approximately 70% (range 48%–88%) for clusters and individual trees. Tree crowns were also successfully delineated on 10-cm spatial resolution digital aerial imagery in forests in western Canada with accuracies between 50% and 100% (mean 80.2%) when trees delineated on the imagery were correctly identified and compared with field measured trees (Coggins et al. 2008). Following crown

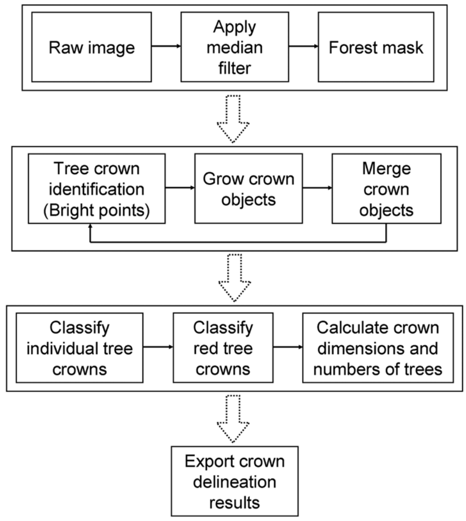

Fig. 2. Flow chart of the crown delineation and individual tree object-based classification algorithm.

delineation, stem diameter and stocking density were estimated from the image derived crowns and also compared to field measurements using t-tests (stocking density: $r^2 = 0.91$, se = 506.65, $p < 0.001$; stem diameter: $r^2 = 0.51$, standard error (se) = 2.63, $p < 0.001$).

Both these studies provide significant confidence in the approach and demonstrate that object-based classification has the ability to accurately define individual trees on remotely sensed data. With the methodology previously demonstrated we applied the same technique to delineate individual red attack tree crowns on the 20-cm spatial resolution imagery using Definiens Developer version 7 (Definiens AG 2007). The object-based classification algorithm (Fig. 2) first identified individual trees within the image; secondly, determined the number of red attack trees; and finally, generated estimates of the total number of all trees and calculate crown areas. A mask was first created to differentiate between forest and non-tree vegetation such as bare ground and roads. The role of the mask was critical as it defined the outer boundaries of tree crowns and aimed to remove shadowing and ground vegetation from the segmentation procedure (Gougeon and Leckie 1999, Pouliot et al. 2002, Bunting and Lucas 2006). Secondly, all non-forested areas in the image were classified by identifying features with bright pixels, e.g. roads, recent clearcuts, and oil and gas landings. Thirdly, all remaining objects were classified as forest and a delineation algorithm was created to define individual tree crowns. To begin the delineation process the brightest objects in the forest class were used to identify as individual tree crowns (Bunting and Lucas 2006). Following identification, bordering objects with similar features were defined and the algorithm was programmed to merge and reclassify these objects into individual tree crowns. Following delineation, tree crowns were classified using four shape criteria, area, roundness, elliptical fit, and the ratio of object length to width, each of which has been proven to be useful when used to classify tree crowns (Bunting and Lucas 2006). Red attack trees were distinguished from healthy trees by applying thresholds to the mean of the red band, the mean of the green band, and red ratio criteria. Every red tree was identified and was used to provide an estimate of the population of mountain pine beetle attacked trees over the area in the image.

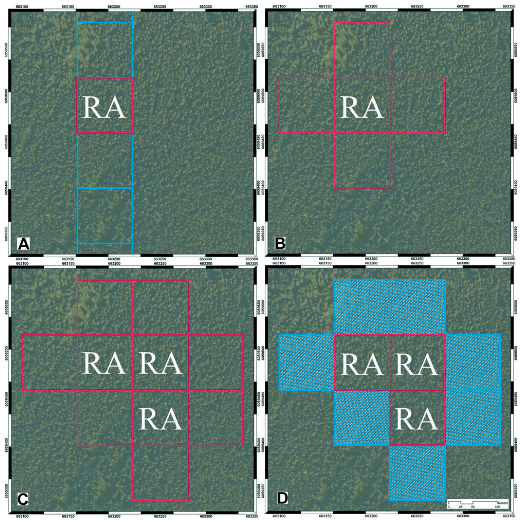

Fig. 3. An example of an initial sample unit located within a grid square in an adaptive cluster sampling design (a). Additional sample units positioned at the cardinal directions of the initial sample unit (b). The final sample network (c) and the edge units which contain no instances of the object of interest (d). The presence of red attack in cells is indicated by RA.

2.4 Phase 2: Adaptive Cluster Sampling

Of the possible sampling options (e.g. simple random, systematic, stratified), adaptive cluster sampling with a line transect approach was utilised in this study. The adaptive cluster sampling is initiated by placing a sample grid over the area of interest from a random starting point. Transect lines are placed at random within the grid and initial sample units are chosen within them where the object of interest (y_i) is detected (Fig. 3a). With adaptive cluster sampling the area sampled is increased, from the initial sample unit containing one or more objects of interest by adding additional units at the cardinal directions around the initial sample unit (Fig. 3b). The object of interest in this study is the number of red attack trees present in each of the networks. Sample units continue to be added according to a predetermined condition of interest C, if for example $C > 1$ then all units adjacent to the initial unit in the cardinal directions are added to sample and the number of units increases in a similar fashion until C is no longer satisfied, the final collection of sample units is known as the sample network (Fig. 3c). The units at the periphery of the sample network which do not satisfy C are also included and are colloquially referred to as edge units (Fig. 3d; Thompson 1990) so the sample has a number of units at the centre that contain the object of interest and are surrounded by a number of blank units.

With adaptive cluster sampling the initial sample size is determined using a simple random sample estimator (Thompson 1990), and lines are placed at random on a square grid throughout an image. The number of line transects were chosen at random using a simple random sample estimator:

$$\text{sample size} = \frac{t^2 \times \text{var}}{E^2} / M \qquad (1)$$

where t is the t-value for a 98% confidence level, E is the acceptable error, in this case 5%, M is the number of grid squares in each transect line (secondary units), and the variance (var) was taken from a study performed within the area

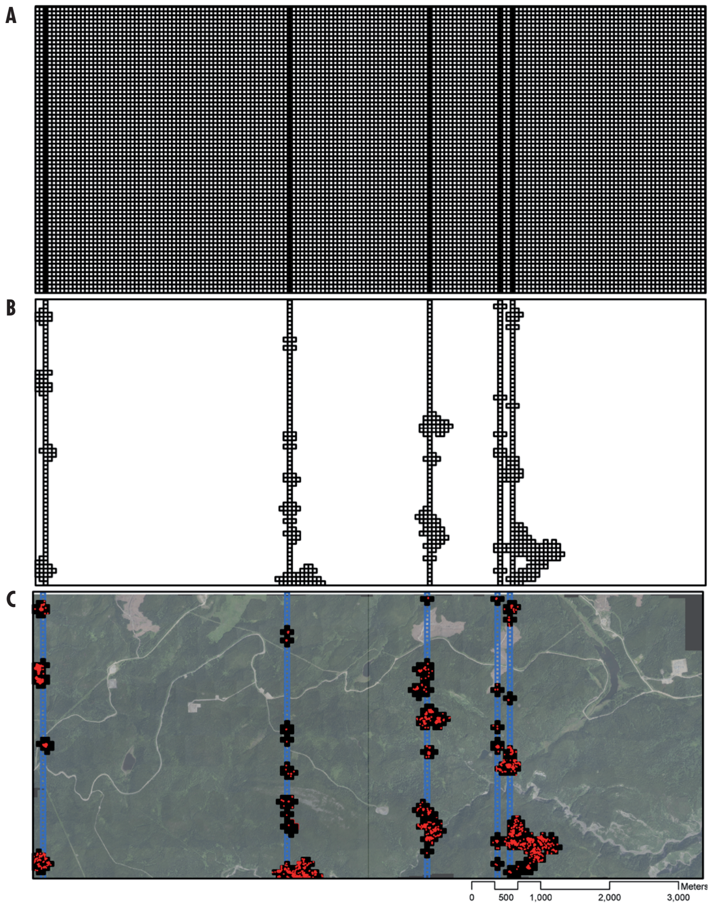

Fig. 4. The initial sample grid of 60 m × 60 m overlaid on the digital remotely sensed imagery with the transect lines shown in solid colour (a). The randomly placed transect lines positioned within the sample area with the sample networks (b) and the resulting red attack crown delineation within the sample networks and transect lines (c).

(Wulder et al. 2009). Variance is calculated using the equation:

$$\text{variance} = \frac{(\text{RA}\max - \text{RA}\min)^2}{4} \qquad (2)$$

where RAmax is the highest number of red attack trees that exist within the study area, and RAmin the lowest number of red attack trees.

To initiate the adaptive cluster sampling approach a square grid comprising of grid squares 60 m × 60 m was overlaid on the digital aerial image (Fig. 4a). The grid squares correspond to the size of field plots used during a reconnaissance of the study area in 2008. Furthermore, mountain pine beetles are known to disperse within a 30-m radius from previously attacked trees (Safranyik et al. 1992). Therefore, this plot size was thought to be suitable to locate mountain pine beetle infestation over the landscape.

Transect lines (primary units) were positioned at random intervals on the sample grid after which mountain pine beetle damage was located within each line (Fig. 4a). Initial sample units were located at each point where mountain pine beetle attack occurred, following which sample networks were built around each sample unit (Fig. 4b). The number of red attack trees in each sample network was obtained using an object based classification technique to first delineate all tree crowns within the sample network and then was trained to focus on the red attack trees only. Estimates of the mean, variance, and confidence limits were calculated using the number of red attacked trees in each network. To estimate the mean and the variance a Horvitz-Thompson estimator (Horvitz and Thompson 1952) is used, which provides an unbiased estimate by dividing each y-value by the probability that unit is included in the sample (Thompson 1991a). For the line transect method this probability is estimated by determining which primary units are likely to intersect network k in the initial sample. This probability is given by:

$$\pi_k = 1 - \binom{N - x_k}{n} / \binom{N}{n} \tag{3}$$

where N is the number of primary units available within the sample grid, n is the number of sample transects used for the study and x_k is the width of the network at the point where the initial sample unit is located within the line transect sample.

This probability is calculated for each network over the sample area, following which the probability that one or more of the primary units that intersect network k and j is included in the initial sample (Thompson 1991a):

$$\pi_{kj} = 1 - \left[\binom{N - x_k}{n} + \binom{N - x_j}{n} - \binom{N - x_k - x_j - x_{kj}}{n} \right] / \binom{N}{n} \tag{4}$$

Where x_k and x_j refer to the width of each network in a pair, and x_{kj} refers to the number of primary units that intersect both networks k and j (Thompson 1991a).

The probabilities calculated by the equations are used to provide unbiased estimates of the mean and variance:

$$\mu_{\text{acs}} = \frac{1}{MN} \sum_{k=1}^{K} \frac{y_k}{\pi_k} \tag{5}$$

$$\text{Var}_{\text{acs}} = \frac{1}{M^2 N^2} \sum_{k=1}^{K} \sum_{j=1}^{K} \frac{y_k y_j}{\pi_{kj}} \left(\frac{\pi_{kj}}{\pi_k \pi_j} - 1 \right) \tag{6}$$

where all variables remain the same as previously described, k is any given network within the population and K is the total number of networks.

The variance estimator can be used to provide estimates of the standard deviation by calculating the square root of the variance estimator. The standard deviation can be used to calculate a range for a confidence interval around the mean. These equations are the basis which provides estimates of the number of red attack trees within a landscape using an adaptive cluster sampling approach.

2.5 Phase 3: Non-Adaptive Approach

In order to assess the efficiency of the adaptive cluster sampling a non-adaptive approach was also utilised, whereby the sample size corresponded to the number of sample units used for the adaptive cluster sampling approach. The sample units were also 60 m × 60 m in size which were randomly placed throughout the sample grid and all these units were run through an object-based classification algorithm to extract the number of red attack trees. To calculate the number of red attacked trees within the landscape using a non-adaptive sampling technique an unbiased estimator of the mean was used:

$$\mu = \frac{1}{Mn} \sum_{i=1}^{n} Y_i \tag{7}$$

where Y_i is the number of red attack trees in the sampling unit and all other variables are described previously. An unbiased estimator of the variance is:

$$\text{var}_{\text{SRS}} = \frac{N - n}{M^2 N n} s_1^2 \tag{8}$$

where

$$s_1^2 = \frac{1}{n-1} \sum_{i=1}^{n} \left(Y_i - M\mu \right)^2$$

As for the adaptive sampling technique, the mean, variance, standard deviation and a confidence range were calculated for the non-adaptive approach.

2.6 Phase 4: Relative Efficiency

Lastly, the relative efficiency of adaptive cluster sampling compared with a non-adaptive approach was calculated. The relative efficiency is calculated by comparing the variance estimates of one sampling technique to the other (Kohl et al. 2006). In this study, the variance of the adaptive cluster sampling approach (var_{ACS}) was compared to the variance of the non-adaptive approach (var_{SRS}):

$$RE = \frac{var_{ACS}}{var_{SRS}} \tag{9}$$

High values indicate the numerator is more efficient than the sampling technique used for the denominator. Comparatively, a value close or equal to 1 suggests there is little difference between one sampling method over the other (Kohl et al. 2006).

3 Results

The adaptive cluster sampling approach was conducted on a 20-cm digital aerial image mosaic covering an area of 40 km^2. With a 60 m × 60 m sample plot size the total number of primary units (N) available was 162, with 69 secondary units (M) contained within each transect line (Table 1). The total number of sample units possible for the area is N * M = 11 178 sample units. To obtain a sample size using equation 1, the maximum number of red attack trees was 155 and the minimum was assumed to be 0, which estimated the variance (from equation 2) to be 1501.56. The number of transect lines (primary units) estimated to provide accurate results was 5 (n). The number of sample units used for the non-adaptive approach was 192, the same number of units utilised in all networks in the adaptive approach.

The object-based classification algorithm indicated red attack tree locations on each transect line. Initial sample units were positioned over each occurrence of mountain pine beetle damage, in total 37 initial sample units were positioned within the transect lines. Sample networks were then built around the initial sample units and the red attack trees were identified within each network by the object-based classification algorithm (Fig. 4c). The total number of red attack trees defined in the networks was 29 635.

The mean number of red attacked trees per hectare located using adaptive cluster sampling was 7.36 trees. The variance was 18.34, and a standard deviation of 4.28 trees per hectare. The confidence limit at the 95% level ranged from –12.45 to 27.18 (the confidence range was 39.63) with $t_{0.05/2,\ 5-1} = 2.776$. The non-adaptive approach had a mean of 61.56 red attack trees per hectare, with a variance of 41.43, and a standard deviation of 6.44 red attack trees. The confidence interval ranged from 40.53 to 82.59 (the confidence range was 42.06) using a t-value of 1.96 ($t_{0.05/2\ 192-1}$). Only 164 red attack trees were delineated in the sample units for the non-adaptive approach. The relative efficiency of the non-adaptive approach compared with the adaptive cluster sampling approach demonstrates the latter gives ($var_{SRS} / var_{ACS} = 2.26$) more than twice the efficiency when estimating the number of red attack trees on the landscape.

Table 1. A summary of input variables and estimates provided by adaptive cluster sampling and the non-adaptive approach.

Variables	Adaptive cluster sampling	Non-adaptive approach
N	162	192
M	69	N/A
n	5	N/A
Number of red attack trees located	29 635	164
Networks	34	N/A
Mean	7.36	61.56
Variance	18.34	41.43
Standard deviation	4.28	6.44
Confidence limit	–12.45, 27.18	40.53, 82.59

4 Discussion

Adaptive cluster sampling is well suited to locate low level infestations and estimate the number of mountain pine beetle attacked trees over large areas. Results indicate the mean and variance for the adaptive technique (7.36 mean and 18.34 variance) are considerably smaller than those estimated by the non-adaptive technique (61.56 mean and 41.43 variance). Similar results were found by Thompson (1991a) who used adaptive cluster sampling with line transects. The high relative efficiency value is caused by the low number of red attack trees determined within the sample units in the non-adaptive technique. Out of 192 sample units only 27 contained red attack trees, the random placement of sample units resulted in areas that were sampled without red attack damage, or were very close to red attack trees but did not encapsulate them. Comparatively to the non-adaptive approach, once initial sample units were determined for the adaptive approach, sampling was concentrated over areas containing mountain pine beetle attack. Therefore, many red attack trees were defined and estimates from these sample networks are less variable than from the non-adaptive approach.

Despite the apparent advantages of cluster sampling to provide estimates of low-level mountain pine beetle attacks there are a number of caveats. First, the final sample size cannot be fully determined prior to sampling because networks are grown during the sampling process. Second, due to the nature of the calculations it is difficult to perform adaptive cluster sampling over very large areas if small area sample units are required. Therefore, the sample unit size must be chosen carefully before sampling is initiated. If however, sample unit sizes are too large, an object of interest will always be contained with the unit, consequently very large areas are sampled and there would be little benefit from conducting adaptive cluster sampling.

Adaptive cluster sampling can be easily applied in combination with most conventional sampling designs, for example this paper used adaptive cluster sampling in conjunction with line transect sampling, where the initial sample points (primary units) are lines. Each line is equally divided into square secondary units and sampling starts with all squares that contain the object of interest (Thompson 1991a). Other examples of variations on adaptive cluster sampling have included; systematic adaptive sampling where the primary sample plots are placed throughout an image or area at a fixed distance apart (Thompson 1991a); double sampling with adaptive cluster sampling where samples are selected in two phases, first an inexpensive first phase sample is selected using adaptive cluster sampling design, then the networks are used to select an ordinary one- or two-phase subsample of units (Felix-Medina and Thompson 2004); stratified adaptive cluster sampling has been used whereby the population is stratified and then networks containing a object of interest are built in each strata following sample plot placement (Thompson 1991b).

The ease by which adaptive techniques are used in conjunction with other sampling designs suggests it would be relatively simple to scale the number of red attack trees from very high spatial resolution imagery to larger areas, using a 2-phase stratified sampling design. This approach could be employed to predict the number of red attack trees over very large areas. Very fine scale (i.e., $<$20-cm spatial resolution) imagery could be used as sample plots within strata in a much larger area and adaptive cluster sampling performed in these images and then extrapolated up to the strata level and finally to the landscape level. Thereby, accurate estimates of the number of infested trees could be provided over very large areas. At the landscape level, inferences could be made regarding the location of red attacked trees and the severity of the attack over the landscape.

The information provided by adaptive cluster sampling can be utilised to provide additional data for mitigation crews, the results from this approach has the potential to provide an approximate number of infested trees per hectare that can be expected. For the purpose of this discussion, detection of infested trees by surveys or through sampling methods implies these trees will be removed during ground surveys. The mean number of infested trees per hectare provides an estimate of the severity and extent of the infestation, the variance around the mean however, provides an indication of the number of trees per hectare that are potentially infested. In this study, the adaptive cluster sampling approach generated a variance of 19 trees per hectare, which indicates that a further 11 infested trees per hectare could exist. If results from adaptive cluster sampling were utilised, mitigation could be completed on 8 infested trees per hectare if strictly following the mean. The trees left undetected and unmitigated will provide a source of beetles to attack and continue infestation the following year. Ground surveys will lessen the potential for infestation to continue, however forests should be monitored in subsequent years to ensure infestations are detected and controlled to keep populations stable or in decline.

Adaptive cluster sampling has the potential to be beneficial when estimating small clusters of mountain pine beetle damage at the leading edge of the infestation. In areas such as western Alberta where the beetle affects trees in small groups adaptive cluster sampling could be used to identify areas of special concern where attack is starting to expand and return statistically sound estimates of the levels of attack and their locations. The spatial locations of attack are especially important as mitigation crews can be guided by this information to help slow the eastward spread of attack. Other advantages to consider when using remotely sensed data in conjunction with this sampling technique include, digital processing of remotely data to enhance and locate all red attack trees, and the ability to extract other data, such as the volume of timber attacked. In areas other than the leading edge, the aerial overview surveys currently utilised are sufficient to gather data on the progress of the infestation. Besides which, these areas generally contain high levels of infestation which would preclude the use of adaptive cluster sampling and also do not require fine-scale estimates of forest health data.

Lastly, adaptive cluster has the potential to determine other rare and clustered events. This approach has been used to idenitify rare tree species (Acharaya et al. 2000), and sparse forest populations (Talvitie et al. 2006) and to predict forest inventory variables (Roesch 1993). The methodology used in this study is applicable to forests globally, to detect rare and clustered populations on the landscape that may be easily identified on remotely sensed imagery. The object of interest could be defined as windblow, root disease, old growth forest, or insect infestations. All of which can be defined on remotely sensed imagery and statistics generated from adaptive cluster sampling to define their populations. Adaptive cluster sampling also has the potential to be combined with conventional sampling schemes, such as stratified sampling. The United States and Canada have large areas of forest cover which are generally homogeneous. However, forests in Europe are distinctly more fragmented and therefore, the landscape could be stratified into land use classes and adaptive cluster sampling used on forested areas to generate information.

5 Conclusion

Adaptive cluster sampling has the potential to be a useful tool to estimate the number of red attack trees over large areas, or particular focus regions, on the landscape. This technique is especially useful at the leading edge of the infestation to identify clusters of low-level mountain pine beetle damage. When compared to a conventional non-adaptive approach, adaptive cluster sampling is demonstrated to be more efficient to assess the number and location of red attack trees on the landscape. Estimates provided by adaptive cluster sampling will provide accurate data to help inform forest managers when making decisions for pest and disease management purposes. This data could guide mitigation to help control infestations, the sample networks provide the location of mountain pine beetle attacked trees and indicate the level of attack severity allowing forest managers to prioritize resources to control outbreaks in highly sensitive or valuable forest stands.

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