Mapping Selective Logging in Mixed Deciduous Forest: A Comparison of Machine Learning Algorithms

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Abstract
This study assesses the performance of five Machine Learning Algorithms (MLAs) in a chronically modified mixed deciduous forest in Massachusetts (USA) in terms of their ability to detect selective timber logging and to cope with deficient reference datasets. Multitemporal Landsat Enhanced Thematic Mapper-plus (ETM+) imagery is used to assess the performance of three Artificial Neural Networks – Multi-Layer Perceptron, ARTMAP, Self-Organizing Map, and two Classification Tree splitting algorithms: gini and entropy rules. MLA performance evaluations are based on susceptibility to reduced training set size, noise, and variations in the training set, as well as the operability/transparency of the classification process. Classification trees produced the most accurate selective logging maps (gini and entropy rule decision tree mean overall map accuracy = 94 percent and mean per-class kappa of 0.59 and 0.60, respectively). Classification trees are shown to be more robust and accurate when faced with deficient training data, regardless of splitting rule. Of the neural network algorithms, self-organizing maps were least sensitive to the introduction of noise and variations in training data. Given their robust classification capabilities and transparency of the class-selection process, classification trees are preferable algorithms for mapping selective logging and have potential in other forest monitoring applications.

Introduction
Various forest monitoring programs are being established to document the status of forest composition and condition over time (e.g., Canada's Earth Observation for Sustainable Development of Forests). Monitoring programs cover large spatial extents, and require sizable quantities of remotely sensed data, thus presenting a unique set of data processing and image interpretation challenges. Aside from the large volume of data to be processed, most complications are related to the paucity of ground reference data caused by cost and time constraints (Wulder, 1998; Loveland *et al.*, 2002). Training datasets used in forest characterization are, therefore, often too small or unrepresentative to capture changes in the spectral variance of forest canopies which exhibit low signal-to-noise ratios in the presence of natural variability and myriad anthropogenic disturbances (Rogan and Miller, 2006). Machine learning algorithms (MLAs) however, offer the potential to handle complex spectral measurement spaces with minimal human intervention and reduced processing time compared to conventional classifiers. MLAs can process large volumes of multi-dimensional data with minimal human intervention and reduced processing time, compared to parametric classifiers such as Maximum Likelihood (Hansen *et al.*, 2000), suggesting their potential suitability in regional-scale forest monitoring. MLA operating characteristics however, are poorly understood by both the remote sensing and ecology communities, thus limiting their potential application in forestry. MLA application is becoming more common, but there is a deficiency of knowledge on their capabilities, limitations, and operation for remote sensing applications in ecology (Kavzoglu and Mather, 2003).

Previous studies have demonstrated MLA effectiveness in generic land-cover change mapping (Lees and Ritman, 1991; Gopal and Woodcock, 1996; Liu and Lathrop, 2002; Chan and Chan, 2002). A recent investigation into the capability of MLAs to accurately characterize land-cover/land-use change (Rogan *et al.*, 2008) identified them as appropriate algorithms when faced with complex measurement space, noise, and heterogeneous remote sensing scenes (Rogan *et al.*, 2003). The literature has not however fully addressed the fundamental problem noted by Gahegan (2003, p. 87): "Difficulty of use is still a real issue with many forms of machine learning." Inadequate understanding of MLA operation, capability, and interpretation has, therefore, resulted in slowed operational acceptance. This paper investigates the capability of three

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Photogrammetric Engineering & Remote Sensing
Vol. 74, No. 10, October 2008, pp. 1201–1211.

0099-1112/08/7410–1201/$3.00/0
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artificial neural networks: Multi-layer Perceptron (MLP), Self-Organizing Map (SOM), and Fuzzy ARTMAP, and two decision trees (Entropy (ENT) and Gini (GIN) splitting rules), to cope with degraded reference datasets for mapping the location of selective timber harvest sites in Massachusetts mixed deciduous forest using multitemporal Landsat Enhanced Thematic Mapper-plus (ETM+) imagery.

Mapping Selective Logging

Regional analysis of the rate and pattern of timber harvesting is critical for estimating carbon budgets, forest productivity, and changes in wildlife habitat (Goulden *et al.*, 1996, Foster and Motzkin, 1998). The prevalent form of logging across the eastern United States is selective rather than clear-cut, which is dominant in the western United States. Kittredge *et al.* (2003, p. 437) describe the logging regime in Massachusetts as having "chronic, moderate intensity." Detection of selective logging at regional scales is one of the most challenging applications of remotely sensed data. Selective logging and thinning results in highly variable levels of canopy damage (spatially and spectrally), that is often confused with undamaged canopy, canopy shading and exposed understory (Rogan and Miller, 2006). Compared to clear-cut logging, remote sensing studies examining selective/partial logging are rare (Gerard and North, 1997).

The detection of canopy gaps using moderate resolution (i.e., 30 m) remote sensing imagery presents several challenges: (a) canopy gaps due to natural disturbance (e.g., windfall, ice damage) present spectral confusion with canopy gaps caused by selective harvesting (Asner *et al.*, 2002), (b) selective harvest gaps are often sub-pixel in scale (Souza *et al.*, 2005), (c) understory exposure and post-disturbance regeneration limit detection by reducing the already subtle change in spectral response between image capture dates (Franklin *et al.*, 2000; Franklin, 2001, and (d) there is no direct relationship between amount of timber extraction and multispectral response (Souza *et al.*, 2005).

Selective logging detection using moderate resolution imagery has focused primarily on tropical rainforest environments (e.g., Periera *et al.*, 2002; Asner *et al.*, 2004; Souza *et al.*, 2005). Asner *et al.* (2004) reported that selective logging increased canopy gap fractions significantly in tropical forest, but anthropogenically induced canopy gap fractions cannot be detected using moderate resolution (30 m) remotely sensed data unless natural canopy gap fractions are less than 50 percent (Asner *et al.*, 2002). Canopy regeneration further complicates the detection of fine scale canopy disturbance; canopy regeneration has been found to reduce canopy gap fraction by 50 percent in as little as one year in tropical forests (Asner *et al.*, 2004). Pereira *et al.* (2002) found a strong relationship between canopy disturbance and the quantity of timber removed in Amazonian rainforests using aerial photographs, but this relationship may not apply when using moderate resolution remote sensing data in temperate, chronically disturbed environments.

Most canopy gaps exhibit lower near-infrared reflectance, and higher visible reflectance when compared to closed canopy (Olsson, 1994). Franklin *et al.* (2000), however, note that canopy gaps can produce an inverse spectral response in areas with significant understory due to increased light availability and subsequent photosynthetic vegetation. This suggests the possibility of a bi-modal change class where both increased and decreased photosynthetic vegetation indicate disturbance in landscapes exhibiting varying understory densities. The detection of selective harvest in Massachusetts forests, using moderate resolution imagery, has not been explored to date.

Selective timber harvesting has been shown to produce subtle changes in reflectance (0.0 to 0.2) when compared to clear-cut harvest (0.2 to 0.14) (Olsson, 1994) but has been successfully detected (up to ~70 percent overall map accuracy) using Landsat Thematic Mapper (TM) data in relatively homogenous forest cover (Franklin *et al.*, 2000; Souza *et al.*, 2005). Selective timber harvesting produces a scene dominated by spatially diffuse felled trees and small (<300 m^2) canopy gaps (Sipe, 1990) in comparison to clear-cut harvest scenes. The detection of selective harvest sites can be described as what Song and Woodcock (2003, p. 2557) refer to as "subtle change detection" and has been identified as "very difficult" (Pereira *et al.*, 2002, p. 282) when using Landsat data. The spatial resolution of data relative to selective harvest sites creates a scene dominated by mixed (harvest/non-harvest) pixels and the broad spectral range covered by Landsat wavelengths can limit the detection of spectrally subtle changes (Asner *et al.*, 2002). Diverse forest species composition and generations of succession since harvest further complicate harvest detection by creating large amounts of inter and intra-class variability (Figure 1). In summary, mapping selective timber harvest in Massachusetts using Landsat represents a challenging classification model appropriate for the rigorous assessment of MLA capabilities.

Machine Learning

Machine learning is a computational approach to data partitioning and categorization that is based on the idea of "learning" patterns in datasets. Within remote sensing, MLAs form a suite of image classification routines ranging from simple K-means clustering to more complex neural networks. The two types of MLA implemented in this work, decision trees and neural networks, are both abstractions of the human learning process but differ fundamentally in their approach: classification trees mimic the human abstraction process through hierarchical categorization while neural networks mimic the brain structure of neurons and linkages.

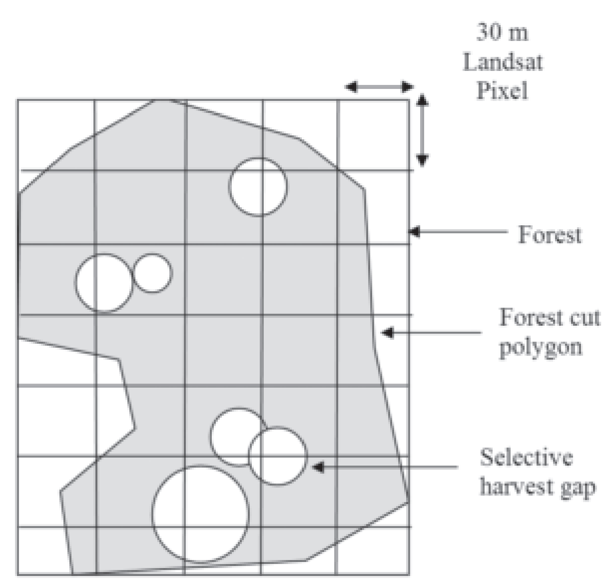

Figure 1. Scene Model: an example scene model of selective timber harvest detection using Landsat Thematic Mapper Imagery.

Neural Networks

Neural Networks are a subclass of MLA that *learn* patterns through a computational abstraction of the human brain's structure, where neuron activation indicates similarity. All networks are based on the concept of the neuron, but differ widely in their structure and, therefore, utility and operation.

Multi-layer Perceptron (MLP)

Multi-layer Perceptrons (MLPs) are a feed-forward artificial neural network calibrated using a back-propagation algorithm. Based on a recursive learning procedure, the MLP algorithm uses a gradient decent search to minimize network training error (Kanellopoulos and Wilkinson, 1997). MLPs are a widely-used and subsequently, extensively researched type of neural network algorithm for remote sensing applications (e.g., Foody, 1995; Foody and Aurora, 1997). MLPs have been employed successfully in change detection and mapping studies (Gopal and Woodcock, 1996; Erbek *et al.*, 2004).

MLPs have three primary components, an input layer, an output layer, and one or more hidden layers; each composed of a user-defined number of neurons. Input layer neurons represent the input variables while output layer neurons represent the classes specified by input training data. There is, therefore, one input layer neuron for each input variable and one output layer neuron for each class specified by the input training data. Input layer neurons and hidden layer neurons are randomly weighted and each training pixel is assigned membership to an output neuron based on maximum activation. This process is repeated iteratively where, at each iteration, the solution is compared to the previous solution, and the weight structure resulting in the lowest testing error is retained. Iteration continues until weights reach a solution producing acceptable testing error for the partition of input variables into the specified output classes, or until the user stops the process. This "trained" network is then used to classify the remainder of the scene based on the level of output neuron activation produced by a given pixel (Foody, 1995).

MLPs regularly produce higher map accuracies than parametric classifiers (e.g., Foody, 2003), but results from studies that compare MLP to other MLAs vary in regard to MLP robustness in different applications (Tso and Mather, 2001). While capable of producing high map accuracies, MLPs have been found overly-sensitive to training parameters and training set size (Gopal and Fischer, 1996; Gopal *et al.*, 1999), prone to overfitting (Spina *et al.*, 1998) (i.e., the network produced is idiosyncratic to the training samples, degrading the ability of the algorithm to generalize training information to the entire image), and to require substantial user intervention during the training phase (Gopal and Fischer, 1996; Gopal *et al.*, 1999) (i.e., input parameters are idiosyncratic to a given dataset, which means the user must monitor convergence and modify parameters empirically).

Attempts to identify input parameter heuristics capable of minimizing the deficiencies presented above have been inconclusive, making "trial and error" necessary for parameter selection until the analyst gains a familiarity with the algorithm's operation (Kavzoglu and Mather, 2003).

ARTMAP

Adaptive Resonance Theory (ART) networks have been shown to minimize sensitivity to training parameters and training set size, overfitting, and the amount of user intervention necessary (Carpenter *et al.*, 1992; Mannan *et al.*, 1998; Liu *et al.*, 2001), indicating their potential promise for the classification of the highly variable measurement spaces indicative to the detection of subtle multitemporal forest change. ANNs utilizing ART (e.g., ARTMAP) have been applied in only a handful of change detection studies (Abuelgasim *et al.*, 1999; Pax-Lenney *et al.*, 2001). ART networks use match-based learning, allowing the retention of significant past learning while still incorporating new information into the network structure (Liu *et al.*, 2001). Unlike MLP, ARTMAP network complexity (i.e., number of neurons) is defined empirically, eliminating the need for *a priori* understanding of data structures. Each input layer (F1) observation (i.e., pixel) is assigned to a category layer (F2) neuron based on its spectral and, if included, ancillary data characteristics. If no F2 neuron meets the similarity threshold of a given F1 observation, a new F2 Neuron is created in order to partition subsets of a degree of homogeneity defined by the user through a "vigilance" parameter (Tso and Mather, 2001). Several researchers have found ARTMAP to outperform MLP (e.g., Carpenter *et al.*, 1998; Mannan *et al.*, 1998; Liu and Wu, 2005).

Self Organizing Maps (SOM)

Kohonen's Self Organizing Map is a neural network procedure in which a single two-dimensional layer of neurons is initialized with random weights and subsequently organized by systematic sampling of the input data. The organization procedure uses progressive adjustment of weights based on data characteristics (similar in concept to a K-means means migration) and lateral interaction such that neurons with similar weights spatially cluster in the neuron layer (Kohonen, 1990; Li and Eastman, 2006). SOMs for supervised classification have two training phases: an unsupervised classification phase in which competitive learning and lateral interaction lead to a fundamental regional organization (topology) of neuron weights (Kohonen, 1990) and a refinement of the decision boundaries between classes based on the training data using a learning vector quantization (LVQ) algorithm (Nasrabadi and Feng, 1988; Li and Eastman, 2006; Li, In Press). Each pixel is then assigned a class of the neuron or neurons most similar in weight structure (minimum Euclidian distance) to the pixel vector of reflectance (Tso and Mather, 2001). Unlike MLP or ARTMAP, Kohonen's (1989 and 1990) SOM acknowledges relationships between classes (i.e., feature map neurons), which allows for the discrimination of multimodal classes, making it a promising method for image classification (Villiman and Merenyi, 2001). Few remote sensing change detection studies have explored SOMs, likely because of their recent introduction to the field. Hadjimitsis *et al.* (2003) used SOM to detect changes in land-cover in the Lower Thames Valley (UK) and found the algorithm capable of accurate image classification and subsequent change detection, but did not quantify the level of accuracy achieved.

Classification Trees (CT)

Classification Trees are a non-parametric technique for data partitioning (i.e., classification) by that recursively split data to form homogenous subsets resulting in a hierarchical tree of decision rules. CTs initially analyze all input variables and determine which binary division of a single variable will most reduce the dependent variable (i.e., classes) deviance of the newly created nodes (Venables and Ripley, 1999), ignorant to future partitions and all previously partitioned training data (Rogan *et al.*, 2003). So while the initial split (i.e., root) is made with all training data, each subsequent split is performed with an always decreasing subset of training data, and is therefore ignorant to samples outside its parent node.

Like ANNs, CTs do not assume a given data distribution and can readily characterize nonlinear relationships, but CTs offer the added advantage of producing interpretable decision rules (Friedl and Brodley, 1997). Several splitting rules have been developed to optimize the efficiency of data partitions and minimize overtraining: (See Zambon *et al.*, 2006 for a complete discussion). Two of the most commonly implemented decision (i.e., splitting) rules are gini and entropy.

Gini

The gini splitting rule is a measure of impurity at a given node. The rule attempts to isolate the largest homogeneous subset of data at each node. The gini rule is defined as:

$$Gini(t) = \sum_i p_i(1 - p_i) \quad (1)$$

where p_i is the relative frequency of class i at node t, and node t represents any node at which a given partition of the data is performed (Apte and Weiss, 1997). Relative frequency is defined as:

$$p_i = \frac{n_i}{\sum_{i-j} n} \quad (2)$$

where n_i represents the number samples for class i, and n represents the number of samples.

Entropy

Entropy (i.e., the "information rule") is a measure of homogeneity of a given node and is calculated as:

$$Entropy(t) = -\sum_i p_i \log p_i \quad (3)$$

where p is the relative frequency of class i at node t (Apte and Weiss, 1997). The entropy rule can be interpreted as the expected value of the minimized negative log-likelihood of a given split result and has been identified as a more accurate discriminator of rare classes than gini (Zambon *et al.*, 2006).

CTs have been widely used for both change detection (Lawrence and Labus, 2003; Rogan *et al.*, 2008) and land-cover classification (e.g., Hansen *et al.*, 1996; Friedl and Brodley, 1997; Lawrence and Wright, 2001). CTs have been found to produce land change map accuracies significantly higher than parametric classifiers (Friedl and Brodley, 1997; Rogan *et al.*, 2002; Rogan *et al.*, 2003).

Study Area

This research focuses on the North Quabbin region in central Massachusetts, USA (Figure 2). The 168,312 ha study site is delineated by township lines to the south and east, the New Hampshire border to the North and the Connecticut River valley to the west. Elevations range from 75 to 487 meters above sea level (Foster and Golodetz, 1997). Soils are predominately sandy loam derived from glacial till (Mott and Fuller, 1967). The average temperature for January and July is −7.33 and 20.72 degrees (C), respectively. The average annual precipitation is 109.47 cm (Massachusetts DHCD, 2001). The region is dominated by non-industrial private forestland, making up approximately 60 percent of the 81 percent total forest. Kitteridge *et al.* (2003) found that North Quabbin Massachusetts forests are disturbed at a rate of 1.5 percent per year due to selective harvesting, but natural disturbance such as ice damage and wind throw also create canopy gaps resulting in a mosaic of natural canopy disturbance (Foster and Boose, 1992). Prevalent tree species include *Quercus rubra* (Red Oak), *Acer rubrum* (Red Maple), *Betula lenta* (Black Birch), and *Pinus strobus* (White Pine). Logging is selective of larger, commercially valuable species such as *Q. rubra* and *A. rubrum* that dominate the canopy overstory.

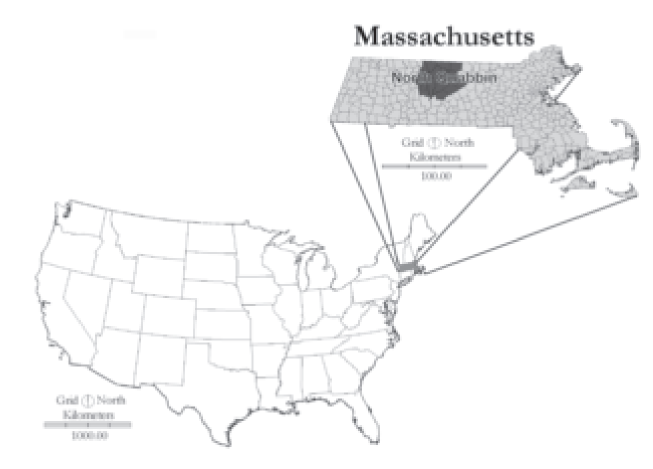

Figure 2. Study Area: The North Quabbin Region, Massachusetts.

Methods

Data

Two Landsat ETM+ images, acquired 31 August 1999 and 08 August 2001 (path/row 13/30) were corrected for atmospheric and solar illumination effects using the Chavez (1996) COS(T) method and converted to reflectance values. Georeferencing of both scenes to 1999 true-color aerial photographs (0.5 m) resulted in a root mean square error below 14 m using 90 ground control points. The images were converted to brightness, greenness, and wetness features using the Kauth Thomas transformation (Kauth and Thomas, 1976). The first Kauth Thomas feature (brightness) has positive loadings in all ETM+ reflectance bands and corresponds to overall scene brightness, or albedo. Greenness, like many other correlates of vegetation amount contrasts visible bands (especially ETM+ band 3) and the near-infrared (ETM+ band 4). Wetness presents a contrast of the visible and near-infrared bands (weak positive loadings) with the mid-infrared bands (strong negative loadings). Spectral features representing multitemporal differences were calculated by subtracting the two sets of Kauth Thomas features to produce change (Δ) in brightness, greenness and wetness. 1999 brightness, 1999 greenness, and 1999 wetness features were input to classification models to provide spectral information representing pre-logging conditions along with Δ brightness, Δ greenness, and Δ wetness.

The dependent variable, locations of selective logging, was derived from a twenty-year (1984 to 2003) record of regulatory timber harvest data, compiled from Massachusetts Forest Cut Plans (FCPs) by researchers at the Harvard Forest Long Term Ecological Research Site (Kitteridge *et al.*, 2002). These data provided ground reference information for MLA training and map validation. The dataset consisted of polygons delineating harvest locations with attributes representing the quantity of timber removed (thousands of board feet), date of harvest, and land ownership category (e.g., private, state, industry, conservation organization) (Kitteridge *et al.*, 2002). FCP polygons have a 70 percent accuracy based on preliminary field verification (Motzkin, personal communication). Further, FCP perimeters are typically within 5 m from the true boundaries (McDonald *et al.*, 2006). FCPs must be reported to state authorities and approved prior to harvesting. Because FCPs are reported for the entire area available for logging prior to harvest, FCP polygon extent often exceeds the extent of actual harvest. To minimize training/validation data error, only FCPs with a removal of over fifty thousand board feet were included as "harvest" in training/validation datasets. The inclusion of only high density removals has been shown to increase detection of harvest when used as ground reference data for remote sensing based change detection (Pereira *et al.* 2002).

FCPs from the year 2000 (January to December) were extracted to limit reference data to pre- and post-logging dates of ETM+ image acquisition. No attempt was made to mask or remove the footprint of selective logging locations for previous dates, i.e., pre-2000. Training data were then further refined to include only pixels that experienced a loss in total greenness between time 1 and time 2 (i.e., negative Δ greenness). Non-harvest training data representing forest and low density residential land-use areas were randomly selected from a fine spatial resolution 1999 land-use map (Massachusetts Department of Housing and Community Development (DHCD), 2001), that were considered stable between 1999 and 2001 (i.e., experienced less than 0.001 change in normalized difference vegetation index (NDVI)). Ten percent of Harvest/Non-Harvest samples were randomly selected and reserved for map validation. The MLA validation dataset consisted of 73 harvest and 1,127 non-harvest sample pixels and a total calibration dataset of 4,144 harvest and 9,720 non-harvest sample pixels.

Algorithm Selection Criteria

MLA evaluation criteria for remote sensing applications have been recently developed (see Defries and Chan, 2000; Pal and Mather, 2003; Rogan *et al.*, 2008). Rogan *et al.* (2008) identifies several evaluation criteria: impact of training set size, effect of variations in training set, effect of noise in the training set, and interpretability of results (i.e., algorithm decision transparency). The criteria identified by Rogan *et al.* (2008) have particular relevance to the detection of selective logging locations because they produce subtle spectral changes, though Rogan *et al.* (2008) investigation focused on more traditional land-cover classification. Large variation in the training dataset and a heterogeneous landscape require an algorithm capable of a range of generalization. Timber harvest records are often scarce and imprecise (Spies and Turner, 1999), making algorithm training set efficiency and resilience to noise especially important. All selection criteria, with the exception of operability/transparency of results, were assessed using the kappa index of agreement (Cohen, 1960) and omission and commission errors. All algorithm tests were conducted using identical training sets. Table 1 presents a summary of all training data configurations.

TABLE 1. TRAINING SET STATISTICS

Variable	Harvest Pixels	Non-Harvest Pixels	Total Sample Pixels
Size 10%	64	1018	1082
Size 20%	696	1993	2689
Size 30%	1317	2965	4282
Size 40%	1456	4000	5456
Size 50%	1905	4993	6898
Size 60%	2276	5945	8221
Size 70%	2491	6849	9340
Size 80%	3305	7760	11065
Size 90%	3693	8756	12449
Size 100%	4144	9720	13864
Stability A	64	1018	1082
Stability B	632	975	1607
Stability C	621	972	1593
Stability D	139	1035	1174
Stability E	449	994	1443
Stability F	371	955	1326
Stability G	215	904	1119
Stability H	814	913	1727
Stability I	388	998	1386
Stability J	451	965	1416
Noise 5%	4384	9480	13864
Noise 10%	4461	9403	13864
Noise 15%	4534	9330	13864
Noise 20%	4754	9110	13864
Noise 25%	4899	8965	13864
Noise 30%	5022	8842	13864
Noise 35%	5180	8684	13864
Noise 40%	5211	8653	13864
Noise 45%	5350	8514	13864
Noise 50%	5466	8398	13864

Training Set Size

Collection of ground reference information on which training sets are based is often time consuming and expensive. The cost of reference data collection and paucity of historical reference information present a challenge to regional forest change assessment. Therefore, it is desirable to use an algorithm capable of producing accurate classifications from minimal training data (Rogan *et al.*, 2008). MLAs have been identified as requiring large volumes of training data when performing classifications (Foody and Aurora, 1997; Pal and Mather, 2003). However, MLAs have also been deemed capable of producing more accurate classifications using small training sets when compared to traditional parametric classifiers (Foody *et al.*, 1995; Gahegan, 2003). Sensitivity to training set size was assessed through incremental training set size reductions (10 percent of total available).

Algorithm Stability

MLAs, particularly ANNs, are often sensitive to subtle changes in training set composition (Defries and Chan, 2000; Simard *et al.*, 2000; Hastie *et al.*, 2001). Small variations in the network calibration sample can result in substantial variation in the network formed caused by differences in the variance captured by the training set. Therefore, it is desirable to identify algorithms that minimize sensitivity to variations in training set composition. Stability was assessed by training each MLA using ten independent sets in order to determine variability in results due to variations in training set composition.

Training Set Noise

Ground reference data are often assumed to represent the *truth* on the ground, despite the likely existence of instrument and human interpretation errors. Therefore, it is desirable for an algorithm to produce accurate classifications in the presence of noise (e.g., intact forest within harvest class training areas) in training data (Defries and Chan, 2000). MLAs are often adversely affected by noise in training sets (Simard *et al.*, 2000). Rogan *et al.* (2008) found that an increase in noise of as little as 10 percent can reduce accuracy by as much as 27 percent overall map accuracy in some MLAs. An algorithm's ability to produce accurate classifications in the presence of training set noise is vital for the selection of an algorithm that could be used operationally. The assessment of noise resilience was conducted through the introduction of randomly mislabeled pixels into training sets in increments of 5 percent, ranging from 5 percent to 50 percent of the total training set.

Operability/Transparency of Results

Many ANNs have been described as "black box" in their operation, providing little to no insight into the relationship between input variables and classification results (Kasischke *et al.*, 2004). Some ANNs have, however, incorporated methods to provide user insight into the decision process (Kohonen, 1990). The ability to interpret results and understand the decision process of an algorithm is an important consideration during algorithm selection because many remote sensing practitioners have been hesitant to implement MLAs due to unfamiliarity with their operation and limited access to specialized software (Chan *et al.*, 2001; Gahegan, 2003; Kasischke *et al.*, 2004). Assessment of operability was based on the intuitiveness of an algorithm's operation and the difficulty of gaining proficiency in algorithm parameter selection. All analyses presented here were conducted using IDRISI Andes; a self-contained GIS and image processing package developed at Clark Labs, Clark University. The amount of explanatory output provided by the algorithm and the usefulness of that output in providing insight into the decision (i.e., classification) process were used as indicators of algorithm transparency.

Results and Discussion

Algorithm Performance

A summary of MLA classification results is shown in Table 2. CTs produced the most consistently accurate overall kappa values (entropy = 0.601, gini = 0.599). SOM yielded a comparable ($p > 0.5$) result (0.597), but ARTMAP and MLP had significantly ($p < 0.0001$) lower accuracies (average overall kappa = 0.487 and 0.408, respectively). CTs consistently underestimated the harvest class (omission errors for entropy and gini = ~14 percent) compared to SOM, ARTMAP, and MLP (omission errors = ~10 to 11 percent), but yielded the lowest commission errors (CT commission error = 5.5 percent). SOM produced commission errors comparable to the CTs, but MLP and ARTMAP substantially overestimated the presence of logging (commission errors = 13.0 percent and 10.3 percent, respectively).

Figure 3 presents the impact of training set size in terms of kappa, omission, and commission errors. CTs were least affected by training set size, as the overall kappa for both entropy and gini splitting rules fluctuated by only 0.064 when trained on ten incrementally smaller training sets. Of the ANNs, SOM proved the most resilient to fluctuations in training set size (overall kappa range 0.092) followed by MLP and ARTMAP (overall kappa range 0.111 and 0.203, respectively). While CTs show little variation when trained on different sample sizes, SOM, ARTMAP, and MLP results indicate clear dependencies on training set size, i.e., SOM and MLP are most accurate when trained on larger sample sizes (i.e., greater than ~5,500 pixels and ~4,500 pixels, respectively).

Results suggest that training set size does not influence CT classification accuracy, provided that samples characterize the feature space exhibited by the classes. ANNs show a clear dependence on training set size, but optimal training set sizes are likely germane to individual classification models. Given limited reference samples, CTs are the MLA of choice. Given availability of large numbers of reference samples SOM may produce more accurate results. CTs were the most stable MLA when compared to SOM, ARTMAP, and MLP. Ten randomly selected independent training sets resulted in a 0.064 fluctuation in overall kappa for both entropy and gini rule CTs. ANNs were less stable; MLP was the least stable (overall kappa range = 0.2567) followed by ARTMAP and SOM (overall kappa range = 0.2137 and 0.1806, respectively). Results indicate CTs to be a more stable MLA for this application and dataset, when compared to ANNs. Despite instability relative to CTs, SOM produced consistently high accuracies and relative stability when compared to the other ANNs.

Figure 4 presents the impact of training set noise in terms of overall kappa, omission, and commission errors. SOM shows more resilience to noise relative to ARTMAP and MLP ($p < 0.0001$), with both exhibiting an increase in error rates as noise is introduced into the training set. CTs were most resilient to noise in the training set. The inclusion of up to 40 percent mislabeled training data in the training set yielded no change in result for entropy and gini splitting rules. The resilience of CTs and SOM's to training set noise can be explained by their initial unsupervised training phase. In order for nodes or feature map neurons to be mislabeled, the majority of training data would have been mislabeled. Since there are only two classes, even when 50 percent of the training set is randomly mislabeled, only 25 percent of

TABLE 2. SUMMARY OF RESULTS FOR VARIATIONS IN TRAINING SET

	SOM	MLP	ARTMAP	CT-Entropy	CT-Gini
Overall Statistics					
Mean Omission (samples)	7.366	8.3	7.566	10.166	10.142
Mean Omission Percentage	10.091	11.369	10.365	13.926	13.894
Mean Commission (samples)	71	147.533	116.3	63.133	63.857
Mean Commission Percentage	6.299	13.090	10.319	5.601	5.666
Mean Kappa	0.597	0.408	0.487	0.601	0.599
Mean Map Accuracy (Producer)	93.47%	87.01%	89.68%	93.89%	94.24%
Size Statistics					
Mean Kappa	0.604	0.445	0.540	0.604	0.595
Kappa Standard Deviation	0.030	0.032	0.053	0.027	0.020
Mean Omission Percentage	8.082	11.369	11.780	14.109	13.972
Mean Commission Percentage	6.326	11.073	7.701	5.510	5.758
Kappa Range	0.092	0.111	0.203	0.064	0.064
Stability Statistics					
Mean Kappa	0.596	0.427	0.543	0.608	0.611
Kappa Standard Deviation	0.064	0.080	0.074	0.027	0.027
Mean Omission Percentage	12.191	12.465	10.273	13.972	13.972
Mean Commission Percentage	6.211	11.987	7.976	5.430	5.350
Kappa Range	0.180	0.256	0.213	0.067	0.067
Noise Statistics					
Mean Kappa	0.593	0.352	0.378	0.591	0.588
Kappa Standard Deviation	0.030	0.052	0.072	0.010	7.97E-09
Mean Omission Percentage	10	10.273	9.041	13.698	10.958
Mean Commission Percentage	6.362	16.211	15.279	5.865	4.755
Kappa Range	0.096	0.177	0.219	0.032	0

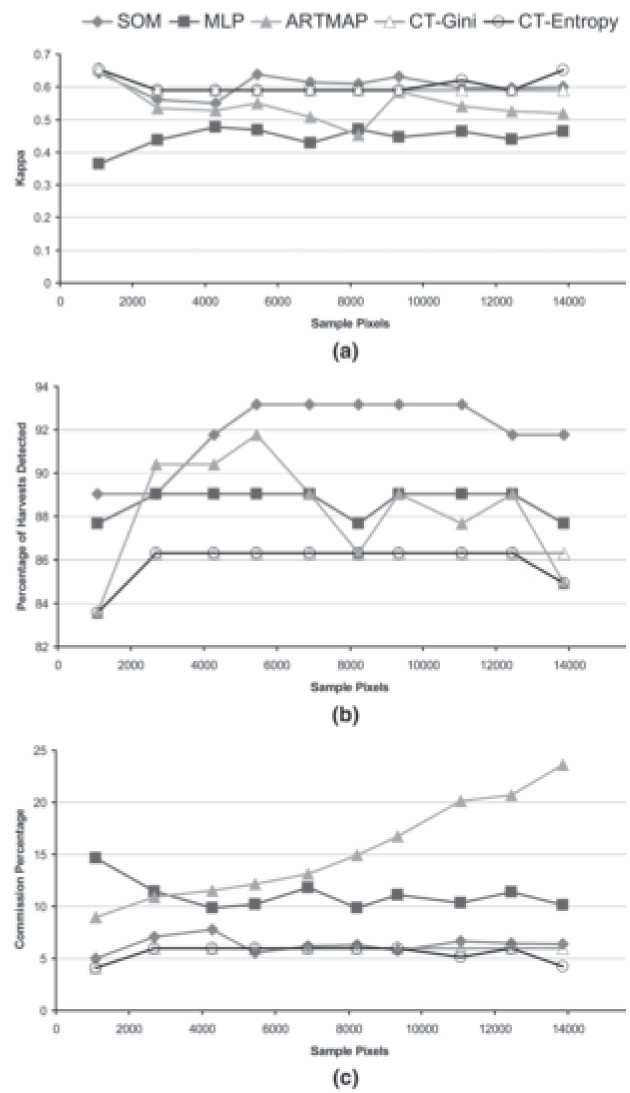

Figure 3. Effect of Variations in Training Set Size: (a) Kappa index of agreement, (b) percentage of harvests sites detected, and (c) percentage of non-harvest sites falsely identified as harvest.

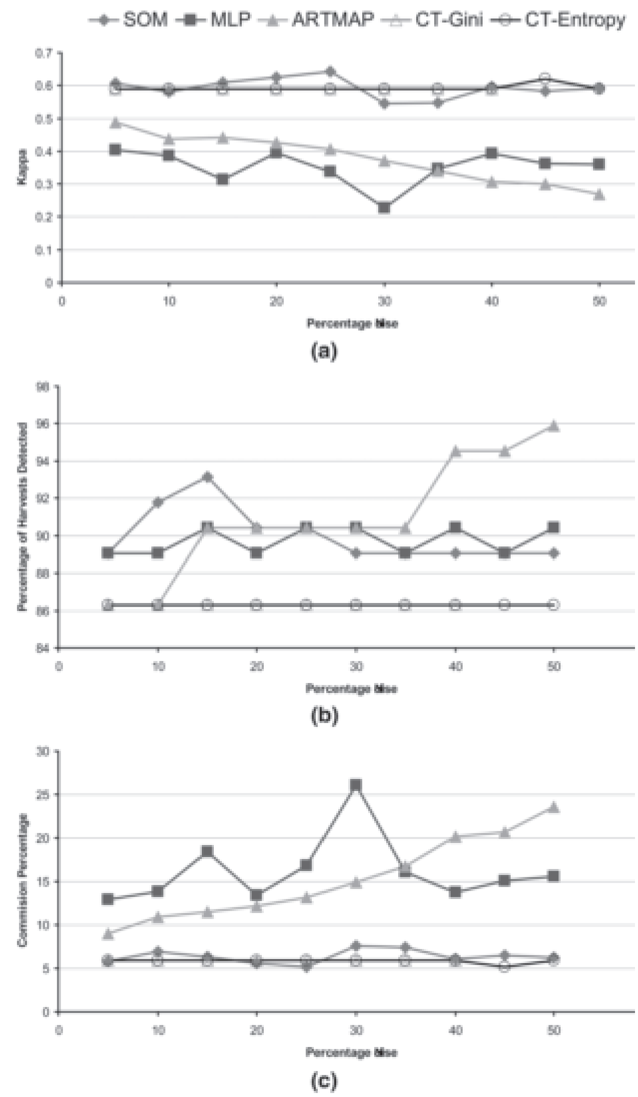

Figure 4. Effect of Noise in the Training Set: (a) Kappa index of agreement, (b) percentage of harvests sites detected, and (c) percentage of non-harvest sites falsely identified as harvest.

the training set is likely to be mislabeled. Therefore, the correct signal still dominates the sample. ARTMAP and MLP are less resilient to training set noise, but for slightly different reasons. ARTMAP also has unsupervised components to its initial network organization (i.e., F2 neurons are created based on image samples, not training data), but it labels F2 neurons as they are created. This can result in F2 neurons being mislabeled based on only a single pixel. The learning retention that is ARTMAP's strength can also explain its susceptibility to training set noise. MLP's susceptibility to training set noise can be explained by its supervised training procedure. The function (i.e., network) fit by MLP is formed based on training data and therefore, attempts to fit the function to the entire training set.

Algorithm Transparency and Interpretability

CTs are the most transparent classification algorithm because their hierarchical decision rules are explicit and interpretable. CT decision rules revealed a heavy reliance on Δ greenness by both splitting algorithms. Δ greenness was selected as the lead split in all instances and the only split in some iterations. Most trees proceeded to split on Δ brightness, 1999 greenness, and Δ wetness, respectively. This variable selection pattern aligns with previously reported CT variable selections in vegetation change detection studies (Rogan *et al*. 2008).

ANNs provide significantly less insight into the algorithm decision process, but each type has features that provide some insight into the network structure. SOM provides insight into the distribution of classes in feature space and potential sources of interclass confusion through the use of a feature map, which displays the multidimensional network-class structure in two dimensional space (Mather, 1999). Inspection of SOM feature maps revealed both the harvest and non-harvest classes as multimodal. MLP can provide insight into its operation through the use of training and testing accuracy information and the output of activation layers. Activation layers can provide per-pixel information about the decision process of the algorithm. Understanding activation layer calculation, however, is difficult, as weight structures are complex and two different weight structures can yield the same result. While training and test accuracy were consistently related to output map accuracy and activation layers did reveal a logical pattern of uncertainly (e.g., edge effects, harvest class uncertainty), hidden layers and weight structures were not found to be interpretable. ARTMAP provides no output to aid in deciphering its decision process other than the number of F2 neurons produced. A high number of F2 neurons relative to the specified vigilance parameter indicate a large amount of intra-class variability in the training samples. For example, introduction of 50 percent noise into the training set consistently increased F2 neurons from ~200 to +10,000 when using an identical vigilance parameter (vigilance = 0.98).

CTs have by the far the most intuitive input parameters. Decision rule and minimum leaf proportion (to prevent overtraining) are the only parameters, and each has clear repercussions on classification results. ARTMAP has the most user-intuitive parameters when compared to the other ANNs examined; parameter adjustments lead to intuitive changes in classification. The vigilance parameter is intuitive in its operation and allows the analyst to specify the precision with which one wants the algorithm to characterize the training data; essentially allowing control over the network's ability to generalize to the remainder of the scene.

User parameters of MLPs are slightly less intuitive than those of ARTMAP and require significant user-intervention. Training an MLP twice using the same input parameters and variables can produce different results, making parameter selection difficult at first. After some experience however, algorithm parameters become intuitive to the user and the necessity for user intervention ceases. Learning rate is the key parameter for manipulation of MLP performance. Adjustment of only the learning rate parameter results in settings approximate to optimal. The version of MLP used for these analyses (IDRISI 15.0 Andes edition) allows for automated learning rate estimation, significantly reducing the amount of user intervention necessary. SOM exhibits the least intuitive relationship between input parameters and output. There does not appear to be a simple method to deduce the optimal settings for a given dataset. However, a wide range of settings can produce robust networks and high relative accuracies.

Selective Logging Detection

Selective logging was successfully detected (>93 percent detection using SOM) using multitemporal Landsat ETM+ data according to Massachusetts FCP records. Figure 5 shows an example of a classification produced by CT (gini). Commission errors as low as ~3 percent and map accuracies as high as 96.16 percent indicate that moderate spatial resolution imagery may offer a cost-effective method of initial landscape sampling for selective logging. Detection of selective logging using Landsat resolution remotely sensed data and minimal human intervention indicates the potential viability of selective harvest monitoring programs in chronically disturbed forests. At such a low cost, a wide area selective harvest monitoring program would have both regulatory and resource management applications.

Selective logging represents a difficult classification problem, due to the heterogeneity of both the harvest and non-harvest classes (e.g., exposed understory and natural variability) and to the paucity of accurate ground reference data. CTs and SOM detected the subtle spectral changes created by the selective removal of individual trees, because they were able to cope with these challenging data characteristics by grouping multiple spectrally heterogeneous clusters into the same class; a characteristic that MLP, ARTMAP, and supervised parametric classifiers do not share. This indicates CTs and SOM to be uniquely qualified for application to a selective harvest monitoring program. While results indicate that harvest location can be successfully identified according to FCP records, further research is required to determine if harvest quantity can be determined from moderate resolution multitemporal remote sensing data. Another important area of research highlighted by these findings is determining whether harvested trees can be distinguished from natural canopy disturbance using moderate resolution remote sensing data.

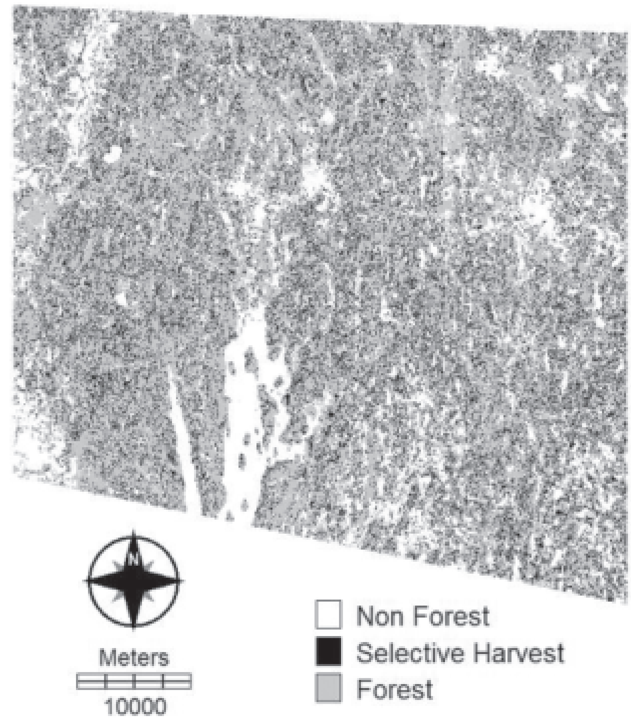

Figure 5. Example Map of Harvest Pattern.

Conclusions

The purpose of this paper was to examine the potential of multitemporal ETM+ data to map selective logging sites in deciduous and mixed-deciduous forest in Massachusetts, USA. MLAs produced classifications of varying accuracy and each exhibited desirable and undesirable traits. CTs and SOM produced the most accurate classifications (mean kappa over all tests ≈ 0.6) and proved to be the most robust classification option when faced with sub-optimal training sets. ARTMAP produced classification accuracies comparable to CTs and SOM under optimal training conditions, but accuracies degrade as training sets reduce in size or noise is introduced. MLP produced classifications of low relative accuracy when compared to the other MLAs assessed (0.12 to 0.2 lower mean kappa) and does not cope well with sub-optimal training sets. It should be noted that these tests were conducted using a scene characterized by subtle and dynamic change in a heterogeneous landscape in order to assess the robustness of the tested algorithms in a "difficult" classification model, and results may vary in a more simple classification model.

CTs have the most user-intuitive parameters (i.e., decision rule and minimum leaf proportion) and the most transparent decision process. ARTMAP also provides intuitive parameters (i.e., vigilance) and relative ease of operation, but provides no insight into the algorithm decision process. SOM user parameters are numerous and not immediately intuitive but it does provide some insight into class and network structure through the feature map. MLP also has several parameters, but many of them can be optimized computationally (i.e., without user intervention). MLP provides minimal insight into network structure and decision process. MLAs encompass a wide range of both capability and usability. In particular, CTs offer a robust classification method for implementation in forest monitoring programs. The coarse-scale characterization of landscape modification presents challenges that some MLAs (CTs and SOM) are well suited for, while others (e.g., MLP) produce unrealistic results (i.e., maps) and unacceptable classification accuracies when presented with sub-optimal training sets. If, as Loveland *et al.* (2002, p. 1098) points out, "The Holy Grail of [digital] change detection is still total automation and high accuracy," then *some* MLAs may be the metal from which that grail will be cast.

Acknowledgments

Harvard Forest's David Foster and Glenn Motzkin provided crucial ground reference data in the form of digitized forest cut plans and expertise on Massachusetts selective logging. Without their support, the research would not have been possible. Clark University's Human Environment Regional Observatory provided funding for the primary author while the research was conducted.

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