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Monitoring the state of a large boreal forest region in eastern Canada through the use of multitemporal classified satellite imagery

O. Valeria, A. Laamrani, and A. Beaudoin

Abstract. Multitemporal classification of Landsat imagery was used to measure and monitor the state of the forest over a large area (11.6 million ha) of boreal forest in eastern Canada using four criteria for a 20 year period (1985–2005). The Enhancement-Classification Method was used in this study. Forty-eight thematic classes based on Canada's National Forest Inventory were identified, then grouped into 13 indicators, and reorganized within four main criteria: (*i*) forest versus nonforest land cover, (*ii*) forest development stage, (*iii*) forest cover type, and (*iv*) forest cover density. Validation based on 2973 high-resolution geo-referenced digital aerial colour photos of the 2005 classified images showed an overall accuracy of the four criteria of 83%, 68%, 58%, and 62%, respectively. The change in each indicator between 1985 and 2005 could be summarized as: (*i*) a decrease in productive forest area of 0.4% (approx. 43 000 ha); (*ii*) a 4.6% decrease in mature stand area, with a concomitant increase in areas classified as vegetated (1.3%) and regenerated (3.4%); (*iii*) concentration of harvesting pressure on coniferous and mixed stands with respective reductions of 8.2% and 0.8%, due to their conversion to deciduous stands; and (*iv*) an increase in low-density stands (3.1%) and a decrease in high-density stands (8.3%). These results demonstrate that medium-resolution (30 m) remote sensing tools can be used both to monitor the state of the boreal forest and to produce key indicators, which were extracted from the multidate Landsat satellite imagery.

Résumé. Une classification multi temporelle d'images Landsat a été utilisée afin d'évaluer l'état de la forêt sur une période de 20 ans (1985–2005) dans une grande région (11,6 millions ha) de la forêt boréale de l'est du Canada à l'aide de quatre critères. La méthode de classification améliorée ECM a été utilisée pour cette étude. Quarante-huit classes thématiques basées sur l'inventaire forestier national ont été identifiées et regroupées en treize indicateurs selon quatre critères: (*i*) forêt non-forêt; (*ii*) stade de développement forestier; (*iii*) type de couvert forestier; (*iv*) densité du couvert forestier. La précision globale à l'aide de 2973 photos couleur à haute résolution pour les images classifiées en 2005 selon les quatre critères a été de 83 %, 68 %, 58 % et 62 % respectivement. Les changements observés pour chaque indicateur entre 1985 et 2005 peuvent être décrits comme suit: (*i*) une diminution de la superficie de forêt productive de 0,4 % (~43 000 ha); (*ii*) une diminution de 4,6 % de la superficie des peuplements matures et une augmentation de la superficie des zones revégétées (1.3 %) et régénérées (3,4 %); (*iii*) une diminution de la superficie des peuplements résineux et mixtes respectivement de 8,2 % et 0,8 % et une augmentation du couvert feuillu due principalement à la succession végétale suite à la récolte forestière et (*iv*) une augmentation de la superficie des peuplements ouverts (3,1 %) et une diminution des peuplements denses (8,3 %). Ces résultats démontrent que les outils de la télédétection multi-spectrale à moyenne résolution (30 m) peuvent être utilisés à la fois pour faire un suivi opérationnel de l'état de la forêt et pour produire des indicateurs clés extraits à partir des images satellites classifiées.

Introduction

The boreal forest of Canada is a highly valuable economic and social resource covering nearly 58% (approx. 6 million km^2) of the country's land mass (CCFM, 2006). Increasing public desire for the sustainable use and conservation of this resource is the driving force behind demands for broad-scale forest monitoring (Secretariat of the Convention on Biological Diversity, 2001). In the Province of Quebec and elsewhere in Canada, growing demand for more timely and accurate information regarding the state of public forests is providing a strong incentive for the development of methodologies that can generate updated exhaustive portraits of forests at regional and sub-regional scales. There is a need to have the capacity to assess the state and change in state of the forest through the monitoring of simple and clear indicators for sustainable forest management (SFM), using methods that are verifiable, specific in

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time and space, and that cover large areas at an acceptable cost (Secretariat of the Convention on Biological Diversity, 2001).

Globally, the concept of forest sustainability has become a leading management paradigm (Duinker, 2000). In Canada, according to the Canadian Council of Forest Ministers (CCFM, 1992), SFM is defined as "management to maintain and enhance the long-term health of forest ecosystems, while providing ecological, economic, social and cultural opportunities for the benefit of present and future generations''. A series of criteria and associated indicators (C&I) is then defined and used to assess the extent to which sustainability is being achieved (Riley, 1995). Establishing a baseline and associated tracking methodology for C&I is important in SFM because it allows monitoring at the reference scale and for coarse scales. This study builds on initiatives that are currently underway across Canada, the broad aims of which are to promote, develop, test, and implement C&I for SFM.

At a regional scale, the boreal forest of northwestern Quebec is one of the most widely studied in terms of both its natural disturbance history (Bergeron et al., 2006) and the dynamics of its forest communities at different scales (Messier et al., 2003; Gauthier et al., 2009). However, the only complete portrait available for this and other forest regions of the Province is the 10 year provincial forest inventory. A regularly updated description of the state of the forest could be used in tandem with the ground-based forest inventory program as a monitoring tool to track forest dynamics, as they are affected by natural processes and human activities. The remoteness and relative inaccessibility of many Quebec boreal forest regions such as Abitibi Témiscamingue (AT) and Nord-du-Quebec (NQ) limits the economic feasibility of intensive and exhaustive ground-based inventory and monitoring (Gillis et al., 2005). A method based on remote sensing would appear to be a more promising alternative under such circumstances.

There are several benefits to using a satellite-based approach to monitor C&I for SFM of boreal forests (Gillis et al., 2005). First, satellite sensors provide coverage of large geographic areas on a repetitive basis (e.g., an individual Landsat-7 image covers 185 km × 185 km). Second, remotely sensed images, especially those offered by the Landsat satellite series, provide demonstrably high-quality continuous time series data at a convenient spatial resolution (30 m for the reflective bands 1–5 and 7) for monitoring purposes (US Geological Survey, 2005), particularly over boreal forests (Sachs et al., 1998; Fraser and Li, 2002; Lunetta et al., 2006; Wulder et al., 2006; van Lier et al., 2011). Finally, satellite images are considered cost-effective for mapping large areas (Franklin et al., 2000) such as the AT and NQ (AT–NQ) region.

The aim of this study was to demonstrate how an operational quantitative assessment of the change of the state of the forest over 11.6 million ha of boreal forest within the AT–NQ region and for a 20 year period could be obtained through the tracking of key SFM indicators that are derived from a temporal series of classified Landsat multispectral imagery. However, quantifying temporal changes that are derived from classified satellite images over such long periods of time and large forest areas remains a considerable challenge for many reasons, owing to the lack of (*i*) a ground-based forest inventory in remote areas for calibration and validation, (*ii*) consistency of inventory methods between management units, and (*iii*) trained personnel and financial resources, as described by Théau et al. (2005), Boudreau et al. (2008) and Wulder et al. (2008b, 2008d), for example. To circumvent these challenges as much as possible, we adopted an operational approach using a post-classification change method applied on multi-temporal Landsat imagery.

This approach is based on the Earth Observation for Sustainable Development (EOSD) national land cover mapping exercise led by the Canadian Forest Service (CFS) (Wulder et al., 2008a, 2008c). In Quebec, a detailed circa 2000 EOSD land cover map made of 48 thematic classes was derived using the Enhancement-Classification Method (ECM). ECM was demonstrated to be successful in (*i*) capturing most forest information that is visible in an enhanced colour composite of three bands from multi-spectral Landsat image and (*ii*) mapping forest land cover classes of large areas without having to rely on extensive and costly training datasets (Beaubien et al., 1999). In addition, ECM was specifically developed for large areas in Canadian boreal environments and was applied successfully in various studies (Beaubien et al., 1999; Peddle et al., 2004; Théau et al., 2005; Boudreau et al., 2008). In this project, the ECM land cover maps with 48 land cover classes were produced for the 1985 and 2005 periods and then linked to SFM indicators to provide post-classification changes in the state of forest.

The main objective of this study was to test and evaluate this approach in association with the effects of available documented drivers affecting long-term forest state changes in AT–NQ. The specific objectives were: (*i*) to map and report forested areas as 13 SFM indicators grouped into four criteria for years 1985 and 2005; (*ii*) to measure the areal change in these SFM indicators over time at the scale of the administrative region and within ecological regions over a period of 20 years (1985–2005); and (*iii*) to evaluate the overall accuracy of SFM indicators, together with error estimates that were related to their variation in areal proportions.

Methods and materials

Study area

The study area covers the whole administrative region of AT and a portion of the NQ, which ranges from 46°12′ N to 50°40′ N and from 74°20′ W to 79°31′ W (**Figure 1**).

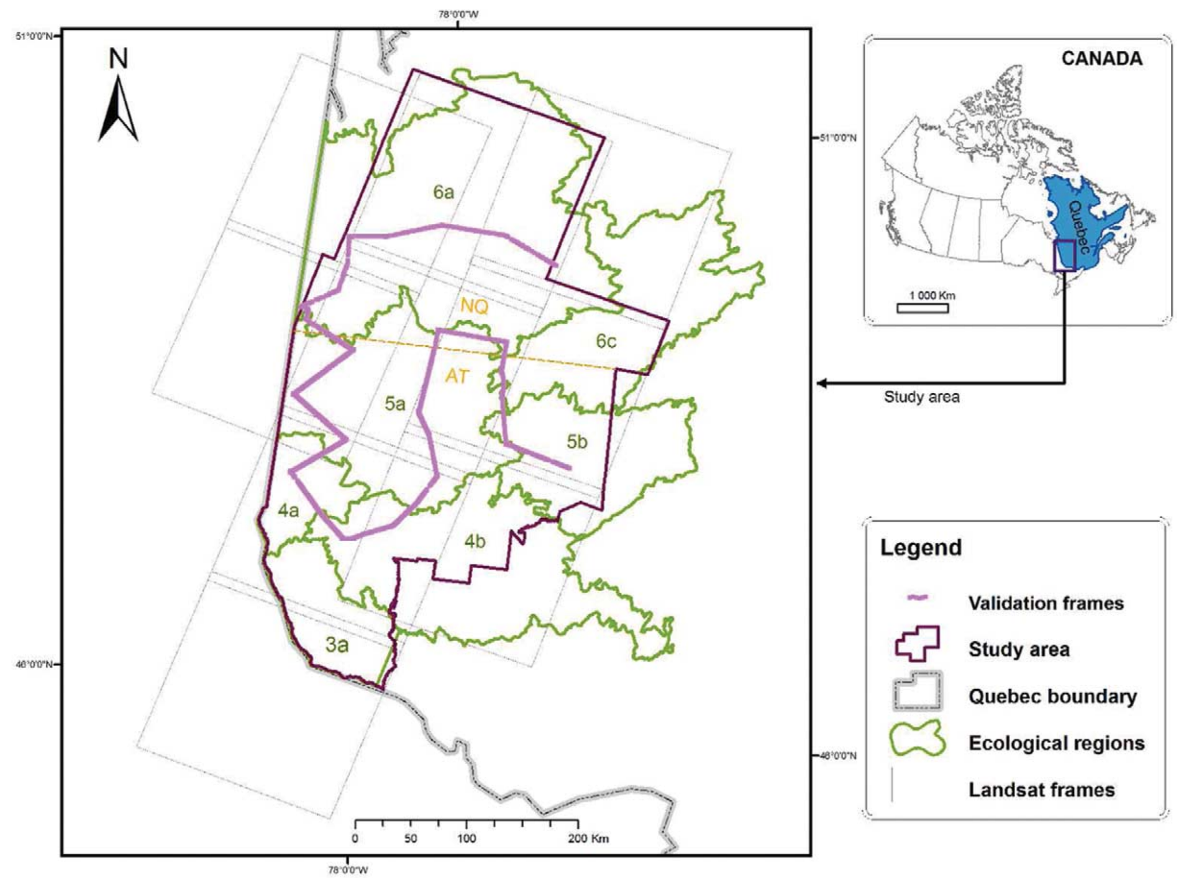

Figure 1. Map of the study area including major ecological regions, satellite imagery boundaries, and the validation frames track. Dashed lines indicate the limit between the Abitibi-Témiscamingue (AT) and Nord-du-Québec (NQ) regions.

This territory covers about 11.6 million ha of the Canadian boreal forest and the Great Lakes – St. Lawrence forest in northwest Quebec. Natural forests are dominated by a mosaic of coniferous, deciduous, and mixed stands along a large climatic and latitudinal gradient. Mature forest is composed mainly of black spruce (*Picea mariana* (Mill.) BSP), jack pine (*Pinus banksiana* Lamb.), trembling aspen (*Populus tremuloides* Michx.), white or paper birch (*Betula papyrifera* Marsh.), balsam fir (*Abies balsamea* (L.) Mill.), and tamarack or eastern larch (*Larix laricina* (Du Roi) K. Koch).

The study area covers seven ecological regions of Quebec: 3a, 4a, 4b, 5a, 5b, 6a, and 6c (**Table 1**, **Figure 1**). A short description of the seven ecological regions that were used in this study and the fraction under Landsat mosaic coverage is summarized in **Table 1**. Each of these ecological regions is characterized by its topography, physiography, climate, and variable proportions of superficial deposit types (Robitaille, 1989).

We chose the study area because of (*i*) the important effects of six decades of logging and fire activities, which resulted in a large gradient of forest structural change from south to north (Perron et al., 2008), (*ii*) the large proportion of the AT–NQ population living in forest-dependent communities and their awareness regarding the necessity of updating the state of the forest, and (*iii*) the availability of circa 2000 products derived from the EOSD mapping project (Wulder et al., 2008a, 2008c). These products included a normalized Landsat mosaic, ground control points (GCPs), forest inventory maps, and other ancillary datasets that were used to produce the EOSD circa 2000 land cover map of the AT–NQ region.

The forest within the study area was shaped by both natural and anthropogenic processes during the period of interest, i.e., 1985–2005. According to data available from the provincial government (Gouvernement du Québec, 1985–2005), wildfire was an important disturbance on an areal basis, with an average 3299 ha per year burned by fires covering a wide range of individual sizes (i.e., from 31 ha to 55 120 ha for 1995). Harvesting of coniferous and deciduous stands was the major disturbance over the landscape, with average areas of 3766 and 821 ha per year, respectively (Gouvernement du Québec, 1985–2005). The construction of a permanent forestry road system has also been a major agent of disturbance. For example, total forestry road lengths for the AT and NQ territories were 1367 km and 2256 km, respectively, in 2005. Unfortunately, forestry road length statistics are not available for earlier dates in these

Table 1. Brief description of the ecological regions covered in the study.

	Ecological region	Bioclimatic domain	Dominant forest cover	Area	
				Total, (10^3 ha)	Studied*, % of total
3a	Collines de l'Outaouais et du Témiscamingue	Balsam fir-yellow birch domain	Mixed stands of yellow birch and softwoods	883	46
4a	Plaines et coteaux du lac Simard		Mixed stands of yellow birch and softwoods	595	100
4b	Coteaux du réservoir Cabonga		Mixed stands of yellow birch and softwoods	1330	49
5a	Plaines de l'Abitibi	Balsam fir-white birch domain	Hardwood or mixed stands with intolerant hardwoods (trembling aspen, white birch and jack pine)	2684	100
5b	Coteaux du réservoir Gouin		Balsam fir and white spruce stands mixed with white birch	905	57
6a	Plaine du Lac Matagami	Spruce-moss domain	Black spruce with occasional balsam fir	3954	81
6c	Plaine de la baie de Rupert		Black spruce	928	44

*% study areas were based on Landsat satellite imagery coverage (pixel counts).

territories, preventing the assessment of road network expansion between 1985 and 2005.

C&I reporting and land cover mapping

A three-step approach was developed to select relevant, feasible, and cost-effective SFM indicators that can be reasonably extracted from classified multispectral Landsat imagery. First, a regional working group, which included representatives of public, private, and academic interests, identified forestry-related issues that were relevant to the main concerns of the public and private sectors. Second, this working group selected a set of 57 relevant indicators from lists of indicators published by the Canadian Council of Forest Ministers (CCFM, 1997), the Canadian Model Forest Network, Natural Resources Canada (2004), and the Ministère des Ressources naturelles et de la faune du Québec (MRNF, 1997). Third, the working group reduced this number to 13 indicators within four criteria (**Table 2**), based on a trade-off between actual remote sensing limitations that were linked mainly to spectral discrimination among indicators and to spatial resolution, these priorities were based on social, environmental, and economic concerns, and budget. The four criteria selected for this study were: (*i*) forest versus nonforest land cover; (*ii*) forest development stage; (*iii*) forest cover type; and (*iv*) forest cover density. The 13 indicators were obtained from the 48 EOSD land cover classes derived from Landsat imagery using ECM.

Multitemporal Landsat datasets and image processing

Multispectral Landsat Thematic Mapper (TM) images containing less than 10% cloud coverage were acquired over AT–NQ for the two time periods (1985 and 2005). When good quality imagery (i.e., low cloud cover and clear sky conditions) from the same year was not available, images from 1984 to 1986 and from 2003 to 2006 had to be used to characterize the 1985 and 2005 periods, respectively. **Table 3** provides spectral bands and acquisition characteristics of the 16 Landsat TM images used in this study, along with their paths and (or) rows and acquisition dates.

The images in this multidate dataset were collected between the end of June and early September, which corresponded to the peak growing season in AT–NQ. Digital values in each image were corrected to top-of-atmosphere reflectance (TOAR) using the procedure of Markham and Barker (1986). Then, images were orthorectified using image-to-image registration with a minimum of 20 GCPs per image, based on Landsat 15 m panchromatic imagery (geogratis web site http://geogratis.cgdi.gc.ca/) and 30 m digital elevation model (DEM) from the National Topographic Data Base (NTDB) (CTI, 2000). The resulting geolocation root mean square (RMS) error ranged between 10 to 20 m. For each time period, differences in atmospheric conditions and vegetation phenology, which resulted from variable acquisition dates during the summer, still affected the TOAR images across the neighbouring Landsat frames. We compensated for these differences by normalizing all images relative to the one with the highest radiometric quality (master scene). Normalization was carried out through a linear regression procedure, which was applied in the overlapping region using a large sample set of pseudo-invariant features (Collins and Woodcock, 1996), including dense mature forest stands, large rock outcrops, few wide roads, and dark lakes. When the master scene did not overlap areas of one of the other scenes, the closest normalized scene was used as a reference. The master scene for both periods (path 18, row 26) was assessed by analyzing the near-infrared (NIR) TOAR reflectance of deep dark lakes. This NIR reflectance is assumed to be negligible in the absence of atmospheric disturbances (Chavez, 1988). For each period, the resulting set of spatially normalized Landsat TOAR images was mosaicked using manually delineated cutlines within PCI Geomatica Orthoengine software. A mask was generated for all haze- and cloud-contaminated areas in both mosaics.

Table 2. Description of the four criteria and indicators of sustainable forest management together with related EOSD land cover classes.

Criterion	Indicators	Description
(1) Forest versus non forest land cover	Productive forest (PF)	Shrubs [10, 14] Regenerating forest areas [11, 12, 13] Revegetating areas [15, 16] Mature and over-mature forests [25, 27, 28, 29, 30, 33, 34, 36, 37, 38, 46] Young forests [26, 48]
	Non productive forest (NPF)	Wetlands dominated by trees [22], herbs [24] or shrubs [23] Sparse forests (10-25% crown closure) coniferous [32, 45], deciduous [35], or mixedwood [42, 43, 44]
	Nonforest (NF)	Rock/rubble [4] Exposed land [5] Urban areas [6] Agriculture [17] Herb [18] Lichen [19] Moss [20] Alpine land [21] Revegetating land [31]
	Disturbed forest (DF)	Recent burned areas (<2 years) [7] Recent clear cuts areas (<2 years) [8]
(2) Forest development stage	Revegetating areas (VA)	Revegetating burned areas (>3 years old) [15] Revegetating cut areas [16] Low shrubs areas [10] (shrubs cover at least 20% of the total area whose height is less than 2 m)
	Regenerating areas (RA)	Regenerating areas dominated by: coniferous [11], broadleaf [12], mixedwood [13] cover and tall shrubs [14] areas (cover more than 20% of the ground whose height is >2 m)
	Mature-over mature stands (MOS)	Medium coniferous forests [27, 28] Open forests: coniferous [29, 30], deciduous [34] or mixedwood [39, 40, 41, 46] Dense forests: dense deciduous [33], mixedwood [36, 37, 38] or coniferous [25]
	Young Stands (YS)	Young closed stands: young coniferous [26] and young deciduous [48] stands (>60% crown closure where trees contribute to more than 75% of the total tree area)
(3) Forest cover type	Mixed stands (MS)	Dense mixedwood stands (>60% crown closure) where the majority is: broadleaf [36], coniferous [37] or 50/50 [38] Open mixedwood: 25–60% crown closure where the majority is: broadleaf [39], coniferous [40] or 50/50 [41, 46]
	Coniferous stands (CS)	Dense coniferous [25, 26] stands (>60% crown closure, coniferous trees ≥75% of total basal area) Medium and open density coniferous [27, 28, 29, 30, 46]
	Deciduous stands (DS)	Dense deciduous stands (>60% crown closure where deciduous trees are 75% or more of total basal area): [33, 48] Open deciduous [34] stands (25-60% crown closure, broadleaf trees ≥ 75% of total basal area)
(4) Forest cover density	Open cover (OC)	Medium density coniferous stands (40-60% crown closure where coniferous contributes to >75% of the total tree area): [27, 28] Open stands (25-40% crown closure; trees ≥ 75% of total basal area): [29, 30, 34, 39, 40, 41, 46]
	Dense cover (DC)	Dense stands (>60% crown closure, trees ≥ 75% of total basal area): [25, 33, 36, 37, 38] Closed young stands: [26, 48] Water: Lakes, reservoirs, rivers or streams [9] No data-null: Non classified areas [0]; Shadow [1]; Clouds/Haze [2]; Snow [3]

Note: EOSD class ID within square brackets.

The resulting masked areas were then excluded from the analysis.

Temporal normalization was finally applied to the resulting circa 1985 and 2005 Landsat image TOAR mosaics to further reduce remaining atmospheric and sensor effects. The original 2000 EOSD normalized Landsat TOAR mosaic over the region was used as a reference data set for this normalization procedure, through a band-by-band linear regression model that was calibrated on a representative sample of pseudo-invariant features covering the largest spectral range possible (Collins and Woodcock, 1996). An independent large sample set consisting of dense mature deciduous covers, which were considered stable between 1985 and 2005, showed that the average differences between the mosaicked TOAR spectral bands of the 2005 and 1985 mosaics were –27.4%, –2.9%, and –7.7% for the red (R), NIR, and mid-infrared (MIR) bands, respectively. Whereas normalization across such a large mosaic was satisfactory for the IR bands, the poorer performance of the red band can be explained by residual haze in some regions, together with phenological differences across the mosaic and between the two dates.

Classification and change detection method

Many approaches have been previously used to detect and monitor land cover changes from multitemporal remote sensing data sets (Yuan and Elvidge, 1998; Espírito-Santo et al., 2005; van Lier et al., 2011). Differencing of spectral bands (Ridd and Liu, 1998), vegetation indices such as the Normalized Difference Vegetation Index (Wilson and Sader, 2002) or Tasseled Cap indices (Healey et al., 2005), principal component analysis (Singh and Harrison, 1985; Du et al., 2002), and multidate classifications followed by post-classification change detection and analysis are the most common techniques that have been employed in remote sensing for change detection (Franklin et al., 2002).

A post-classification change detection approach (Hall et al., 1991; Yuan and Elvidge, 1998) was selected for this study, considering the circa 2000 EOSD land cover map would serve as a convenient and appropriate baseline map. However, such an approach is vulnerable to classification errors, which are inherently difficult to characterize. Moreover, they propagate across time potentially leading to poor results in land post-classification analysis. Therefore, we estimated classification errors that were associated with temporal changes in indicator area proportions as a means of evaluating the strengths and limitations of post-classification change analysis in the context of our study.

The post-classification approach is based on ECM, which captures most of forest information in a linearly enhanced Landsat colour composite of NIR (band TM4), MIR (band TM5), and R (band TM3) spectral bands (**Table 3**). Then, it converts the spectral information into thematic classes through a "hybrid" classification routine that uses both unsupervised and supervised *k*-means clustering (Beaubien et al., 1999). By using a supervised iterative generalization process with modal filters, marginal clusters can be eliminated, which ultimately produces a reduced number of significant clusters (typically 70–90) that can be handled efficiently by a knowledgeable analyst for class labelling purposes.

The ECM used in this study consisted of the following steps: (*i*) digital linear contrast enhancement of the normalized and mosaicked TOAR spectral bands (TM4, TM5, and TM3), which maximized visual discrimination among forest classes; (*ii*) classification of the enhanced image through unsupervised *k*-means clustering, which resulted in about 150 spectral clusters; (*iii*) reclassification of the enhanced image on the basis of selected signatures using a minimum distance function; (*iv*) aggregation by a trained analyst of the resulting spectral clusters (approx. 70–90 classes) into 48 thematic land cover classes, based on a detailed version of the EOSD classification legend (Wulder et al., 2006); and (*v*) usual post-classification filtering using a modal filter with a 3 × 3 kernel (90 m × 90 m, i.e., about 1 ha) to smooth out the classified pixels and obtain the locally dominant land cover class.

Forty-four of the 48 EOSD classes that were present within AT–NQ region were assigned to one or more of the

Table 3. Characteristics of the satellite scenes used in the study.

Time periods	Acquisition date	Path/Row	Mission, sensor	Spectral bands*	Spatial resolution
1985	22 June 1984	17/26			
	22 June 1984	17/27			
	21 July 1986	17/28			
	21 July 1986	18/25			
	21 July 1986	18/26			
	21 July 1986	18/27			
	21 July 1986	18/28			
	07 Aug 1984	19/26	Landsat-5,	Band TM3: Red Band	30 m
2005	07 Sept 2006	17/26	TM (Thematic Mapper)	TM4: near IR	30 m
	07 Sept 2006	17/27		Band TM5: mid IR	30 m
	06 July 2004	18/25			
	26 Aug 2005	18/26			
	26 Aug 2005	18/27			
	25 July 2005	18/28			
	13 Sept 2003	19/25			
	30 June 2005	19/26			

*TM3, TM4, TM5 (RGB) used in ECM classification

13 indicators (**Table 2**). For instance, class 25 (dense mature coniferous) was assigned to four indicators, i.e., dense cover (DC), coniferous stands (CS), mature–over-mature stands (MOS), and productive forest (PF). In contrast, class 8 (recent burn) was assigned to the single indicator, disturbed forest (DF). The remaining three classes (0, 1, and 2 for no data, clouds, and cloud shadows, respectively) were aggregated into a ''no data'' class. The water class 9 was kept as is.

Each of the 13 indicators was allocated to one of the four criteria, as shown in **Figure 2** as dark grey boxes. White boxes refer to the no data and water classes, which were not assigned to any of the four criteria. The four criteria, together with their related indicators, are hierarchically imbedded from right (high-level) to left (low-level) (**Figure 2**). For example, the PF indicator within criterion 1 (forest versus nonforest land cover) is divided into four indicators within criterion 2 (forest development stage). In this latter criterion, the indicator MOS is split into three indicators (mixed stand (MS), CS, deciduous stand (DS)) within criterion 3 (forest cover types). Finally, indicator MS is further divided in two indicators (open cover (OC) and dense cover (DC)) within criterion 4 (forest cover density). It should be noted that light grey boxes represent an aggregation of indicators, when they become irrelevant for the lower level criteria. For example, because criteria 2, 3, and 4 are only relevant to productive forests, we aggregated nonproductive forest (NPF), nonforest (NF), and DF into NPF + NF + DF.

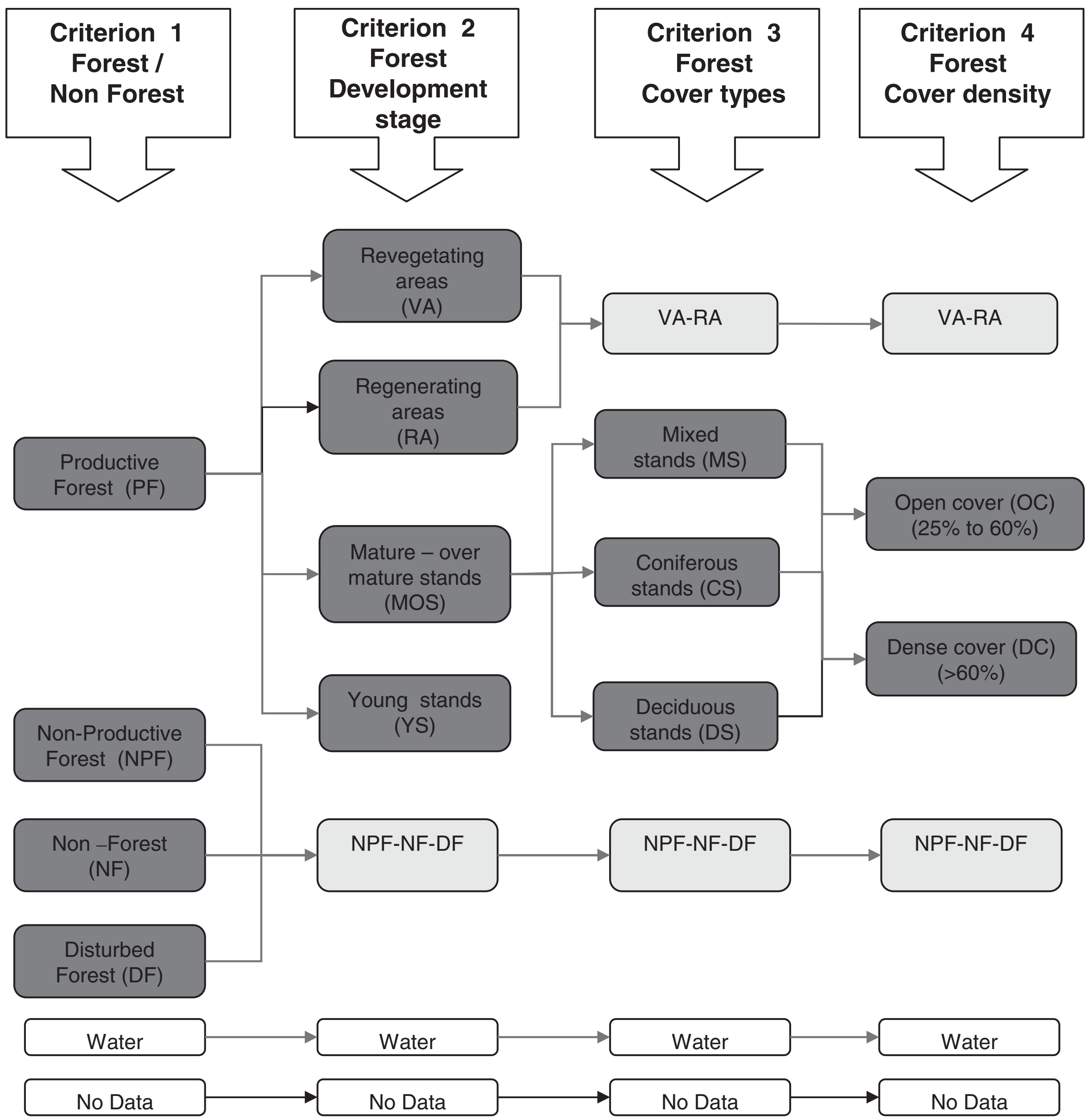

Figure 2. Selected criteria and their indicators (dark grey boxes). Grey boxes represent an aggregation of indicators while white boxes indicate indicators used only for assessment of accuracy and for mapping purposes.

This hierarchical structure was used for statistical compilation across the mapping area. The no data and water classes were used for mapping and accuracy assessment but were excluded from the statistical compilation and analysis. Total area in ha and percent area of the territory for criteria and indicators were generated, respectively, for 1985 and 2005 across the whole study area and for the six constituent ecological regions (**Table 4**).

Accuracy assessment of the 2005 classification

Reference data collection

The accuracy of the indicators, as mapped from the 2005 Landsat mosaic, was assessed using 53 000 fine-resolution geo-referenced digital aerial colour photo frames, each covering about 14 ha. The frames were acquired during the summer of 2005 using the Geo-3D system (http://www.geo3d.com/). Acquisition was done along flight lines laid across ecological, temperature (north–south), and precipitation (east–west) gradients within the study area, thereby capturing most of the variation in spectral properties that were associated with the 48 EOSD thematic classes. The sum of all flight lines was about 1000 km, with a swath width of 370 m. For purposes of data handling efficiency, we sub-sampled the frame database, with the number of frames that were to be selected (2973 frames) determined from Equations (1) and (2) (Cochran, 1977; Wulder et al., 2007)

$$n = \left[\left(\frac{z}{m} \right)^2 \right] \times p \times (1 - p) \tag{1}$$

where z is the percentile of the standard normal (1.65 for a 90% confidence interval), m is the margin of error (0.03), and p is the assumed population proportion (0.8). Half of the 2973 frames were then selected randomly from the full-frame database in proportion to the area of ecological region that each class covered within the main transect (except region 3a). The remaining half was selected as being representative of the area that was covered by the rarest classes, based on Czaplewski and Patterson (2003)

$$n_i = [p_i \times (n/2) + (1/k) \times (n/2)] \tag{2}$$

Table 4. Error measures of indicators based on confusion matrix of circa 2005 classified Landsat imagery.

Criterion	Indicator	Ecological Regions						Overall Region (AT + NQ)		
		4a	4b	5a	5b	6a	6c	Producer's accuracy (%)	Overall accuracy (%)	K ± confidence interval (%)
		Indicator producer's accuracy and standard error (%)								
1	PF	93 (1.1)	99 (0.6)	93 (0.7)	94 (2.0)	80 (2.1)	98 (1.7)	87	83	63 ± 3.3
	NF	67 (19.2)	0	87 (3.2)	*NA*	67 (12.2)	*NA*	76		
	NPF	*NA*	27 (11.4)	37 (3.9)	0	75 (5.0)	0	54		
	DF	0	50 (25.0)	27 (6.0)	25 (15.3)	36 (14.5)	0	31		
	Water	100 (0.0)	83 (7.0)	91 (3.0)	73 (11.4)	81 (7.5)	60 (21.9)	86		
2	VA	*NA*	7 (6.9)	18 (5.7)	20 (12.6)	36 (10.3)	0	24	68	49 ± 2.7
	RA	7 (6.4)	14 (6.4)	30 (3.7)	13 (11.7)	41 (6.0)	25 (21.7)	34		
	YS	0	0	2 (1.1)	0	6 (4.0)	0	5		
	MOS	99 (0.9)	98 (0.9)	95 (0.8)	91 (2.8)	80 (2.7)	100 (0.0)	88		
	NPF+NF+DF	64 (14.5)	30 (8.4)	59 (0.0)	22 (9.8)	73 (4.3)	17 (15.2)	63		
	Water	97 (3.2)	69 (7.8)	86 (3.5)	73 (11.4)	85 (7.1)	60 (21.9)	84		
3	VA+RA	16 (6.1)	30 (6.9)	34 (0.0)	50 (11.8)	45 (5.1)	33 (19.2)	40	58	48 ± 2.2
	DS	49 (6.6)	41 (6.9)	43 (3.2)	20 (8.9)	40 (8.9)	0	39		
	CS	37 (7.5)	50 (7.7)	56 (0.0)	60 (6.6)	58 (3.9)	90 (4.3)	57		
	MS	81 (4.1)	85 (3.1)	77 (2.5)	56 (7.4)	53 (6.8)	53 (12.1)	66		
	NPF+NF+DF	54 (13.8)	29 (8.2)	59 (0.0)	21 (9.4)	74 (4.2)	14 (13.2)	63		
	Water	100 (0.0)	62 (7.8)	84 (3.7)	69 (11.6)	85 (7.1)	60 (21.9)	82		
4	VA+RA	16 (6.1)	28 (6.6)	34 (3.2)	47 (11.5)	46 (5.2)	40 (21.9)	41	62	47 ± 2.4
	OC	21 (4.6)	28 (4.9)	56 (2.4)	52 (6.5)	63 (4.0)	52 (8.7)	55		
	DC	93 (2.5)	94 (2.1)	73 (1.9)	67 (6.1)	59 (5.0)	84 (5.9)	72		
	NPF+NF+DF	50 (13.4)	30 (8.4)	59 (0.0)	22 (9.8)	71 (4.3)	11 (10.5)	62		
	Water	100 (0.0)	67 (7.9)	86 (3.6)	69 (11.6)	81 (7.5)	60 (21.9)	83		
No. of labelled samples		269	335	1631	173	475	90	2973		

Note: Producer's accuracy with standard error (within brackets) at ecological region scale; producer's accuracy, overall accuracy and Kappa coefficient (K) at regional scale; *NA*, not enough data available for validation. Grey boxes highlight producer's accuracy ≥ 60% (except for water).

where n_i is sample size of sub-set mapped stratum i, p_i is the proportion of sample population mapped as i, n is the total sample size, and k is the number of ecological regions.

Reference data labelling process

The geo-referenced 1 ha central area of each frame of the sub-sample was analyzed and labelled within a two-phase process carried out by three independent experienced interpreters, as in Wulder et al. (2007). Labelling of this reference data set was done according to the 48 EOSD land cover classes. During a first phase, two interpreters independently labelled each frame central area. Occasionally, interpreters had to select a dominant and secondary class label based on the relative occurrence of two classes observed within the central area. When the two photo interpreters agreed on the labelled class, this class was used as the reference datum. When they disagreed, the second phase of interpretation was initiated and a third interpreter intervened to obtain a majority vote for a class label. In rare cases where all of the interpreters disagreed on the labelled class, the labelling provided by the most experienced interpreter was used.

Validation was done for the entire study area region and for individual ecological regions for the four criteria and 13 indicators that had been obtained from the classified circa 2005 Landsat mosaic. These indicators were based on the referenced labelled aerial digital photo frames acquired in 2005, using conventional contingency tables (or confusion matrices) that were derived from among the set of indicators for a given criterion. We used the dominant Landsat-derived indicator over a 3 pixel $\times$ 3 pixel window to take into account possible geo-localization mismatches between the aerial photos and Landsat imagery. Overall accuracy, producer accuracy with standard errors, and Kappa (K) coefficients of agreement (with confidence intervals) were generated for each indicator or criterion following Banko (1998).

Error estimation of indicator area proportion change between 1985 and 2005

Unfortunately, appropriate high-resolution datasets that are comparable in terms of their geometric and radiometric quality to the one from 2005 were not readily available as geo-referenced product for validating the classified 1985 Landsat mosaic. Consequently, we considered that classification accuracy in 1985 was similar to that of 2005, based on the assumption of high consistency in the classification process that was applied by the same trained analyst over the two mosaics. To support this assumption, we estimated the error associated with temporal change in the areal proportion of each indicator (%) from 1985 to 2005, in part by using the method of Hall et al. (1991), which relied on the confusion matrix and percent occurrence of indicators by region in each classified mosaic

$$\begin{aligned}
&\mathrm{err}(i) = \Delta p(i) - \Delta P(i)\\
&\text{with}\\
&\Delta p(i) = p_{05}(i) - p_{85}(i), \Delta P_i = P_{05}(i) - P_{85}(i)\\
&P_{85}(i) = \sum_{j=1}^{n} C_{05}(i|j) \times p_{85}(j), P_{05}(i) = \sum_{j=1}^{n} C_{05}(i|j) \times p_{05}(j)
\end{aligned} \tag{3}$$

where $\Delta p(i)$ and $\Delta P(i)$ are the variations in areal proportion (%) for indicator i, respectively, from the classified change and "true" change; subscripts 85 and 05 refer to the classification year; n is the number of indicators for a given criterion; and $C_{05}(i|j)$ is the conditional probability of a true indicator i to be classified as indicator j as given by the 2005 confusion matrix. For each year, we independently corrected the classified proportion $p(i)$ of indicator i to derive an adjusted ("true") proportion $P(i)$ based on the confusion matrix of 2005. Thus, the error err(i) associated with areal change is the difference between the classified versus the "true" areal change. It should be noted that we analyzed indicator change overall for a given region and not on a pixel-by-pixel basis through a transition matrix. At this stage, we did not apply the complete transition error model as implemented by Hall et al. (1991) nor did we consider standard error estimates for Equation (3).

Results

Accuracy assessment of indicators

For the various indicators, **Table 4** includes overall and producer accuracy, standard errors, and confidence intervals for K at the regional and ecological region scales (2005). At the regional scale, forest versus nonforest land cover criterion had the highest overall accuracy, i.e., 83%, with a K of 63% $\pm$ 3.3%. Producer accuracy of the DF indicator mainly contributed to maintaining lower values of the K coefficient. The overall accuracy that was obtained for forest development stage criterion was 68%, with K equal to 49% $\pm$ 2.7%. Individual indicators that were in an early stage of development had the lowest producer accuracy, revegetating areas (VA) = 24%, regenerating areas (RA) = 34%, and young stands (YS) = 5%. These three indicators contributed to low overall accuracy for criteria 2 (68%), 3 (58%), and 4 (62%). Overall accuracy of the forest cover type criterion was lowest at the regional scale (58%), with a K of 48% $\pm$ 2.2%. Overall accuracy of the forest cover density criterion was 62%, with K equal to 47% $\pm$ 2.4%.

At the scale of ecological regions, the indicators PF, NF, MOS, MS, and DC show trends in producer accuracy ($\geq$ 60%) that were similar to those at the regional scale.

The indicators DF, VA, RA, and YS exhibited the lowest producer accuracy and highest relative standard errors among all indicators and, consequently, they explained the lowest values observed at the regional scale. Ecological regions 6c and 5b had the lowest number of labels that could be used for validation (90 and 173, respectively) but had the same indicators (PF, MOS, CS, and DC) with high producer accuracy scores ($\geq$ 60%). Water exhibited higher producer accuracy than did the aggregated indicators (NPF + NF + DF and VA + RA). Because of budgetary constraints, no validation data (digital aerial photo frames) were available for ecological region 3a, which was located at the southern portion of the study area (**Figure 1**).

Changes in indicators between 1985 and 2005 at regional and ecological region scales

Area and areal proportion statistics of criteria and indicators for the 1985–2005 time period, at both regional and ecological region scales, are presented in **Table 5**. Areal proportions that were adjusted following Equation (3) have not been reported, but errors and their effects on indicator trends are subsequently discussed.

At the regional scale, our results show that 1985 was dominated by PF (73.1%) and was composed of MOS (65.3%). CS, MS, and DS indicators covered 30.6%, 30.5%, and 5.6% of the study area, respectively. DC and OC indicators represented 46.1% and 20.6% of the productive forest, while water and no data covered about 12.3% of the study area. As shown by indicators and based on knowledge of forest dynamics in the area, the study area has undergone significant changes between 1985 and 2005. PF, DF, and NF decreased by about 43 000 ha, 21 000 ha, and 13 000 ha, respectively, between 1985 and 2005, while NPF increased by about 161 000 ha (14.4%) over the same time period. During this 20 year period, the proportion of CS decreased significantly by 26.8% when compared with itself, and by 8.2% when compared with the territory as a whole, based on 2005 data. MS declined by 2.6% over the 20 year period, while YS decreased by 36.5%. In addition, the percentage of MOS decreased by 7.0%, or 530 000 ha. In contrast, the highest increase (70.8%) occurred in the proportion of DS, when compared to itself. Other indicators such as VA and RA increased noticeably, by 114.9% (148 000 ha) and 63.5% (396 000 ha), respectively, during the same period. An increase of 15.4% in OC and a

Table 5. Indicator area and areal variation at regional and ecological region scales for 1985 and 2005. Indicator area variation relative to the whole territory is indicated between brackets.

Criterion Indicator	Overall Region (AT + NQ)						Ecological Regions						
							3a	4a	4b	5a	5b	6a	6c
	1985		2005		1985–2005		1985–2005						
	Indicator area				Indicator area variation		Indicator area variation						
	Area, 10^3 ha	Relative area (%)	Area, 10^3 ha	Relative area (%)	Δ area, 10^3 ha	Relative Δ area (%)	Relative Δ area (%)						
1													
PF	8497	73.1	8454	72.7	−43	−0.5 (−0.4)	1.5	0.8	0.8	−0.1	0.7	−1.4	−3.0
NF	398	3.4	384	3.3	−13	−3.4 (−0.1)	102.7	3.5	230.1	9.6	19.9	−52.5	173.3
NPF	1118	9.6	1279	11.0	161	14.4 (1.4)	92.1	1.4	33.6	5.7	57.8	16.2	15.2
DF	182	1.6	161	1.4	−21	−11.4 (−0.2)	−69.7	−59.3	13.5	−47.3	−38.2	−34.0	361.9
Total	**10195**	**87.7**	**10278**	**88.4**									
+ Water & No Data	**1430**	**12.3**	**1347**	**11.6**									
Total territory	**11625**	**100.0**	**11625**	**100.0**									
2													
VA	129	11.1	277	2.4	148	114.9 (1.3)	−13.8	−35.8	42.7	−9.7	11.9	138.0	1281.3
RA	624	5.4	1020	8.8	396	63.5 (3.4)	−59.8	−71.4	62.6	−18.9	286.7	152.7	4712.1
YS	159	1.4	101	0.9	−58	−36.5 (−0.5)	20.1	−23.1	123.2	−60.3	181.5	−48.3	−63.5
MOS	7585	65.3	7055	60.7	−530	−7.0 (−4.6)	5.3	20.7	−2.3	6.3	−8.0	−15.6	−31.9
Total	**8497**	**73.1**	**8454**	**72.7**									
3													
DS	646	5.6	1103	9.5	457	70.8 (3.9)	7.6	161.6	24.5	87.7	258.3	278.9	1936.0
CS	3556	30.6	2604	22.4	−953	−26.8 (−8.2)	64.3	−22.7	11.7	−26.8	−7.5	−29.1	−44.4
MS	3541	30.5	3449	29.7	−93	−2.6 (−0.8)	0.5	−1.4	−8.5	1.2	−14.7	7.4	−5.7
Total	**7744**	**66.6**	**7156**	**61.6**									
4													
OC	2391	20.6	2760	23.7	369	15.4 (3.1)	−34.1	−30.0	−15.7	47.6	124.9	−1.3	202.4
DC	5353	46.1	4396	37.8	−957	−17.9 (−8.3)	10.1	40.5	1.2	−13.3	−24.8	−34.9	−61.6
Total	**7744**	**66.6**	**7156**	**61.6**									

decrease of 17.9% of DC over 20 years was observed. Total area covered by mosaic Landsat images was equivalent between the two years.

At the ecological region scale (**Table 5**), the change of state of the forest over 20 years resulted from both natural and anthropogenic processes. Consequently, pressures on the boreal forest have affected the study area differently from one ecological region to another. Three ecological regions (4b, 5a, and 6a) drive the whole territorial trend because they cumulatively represent over 70% of the total area under study. Ecological regions 6a and 6c showed the highest decline in PF (1.4% and 3.0%, respectively), whereas ecological regions 3a, 4a, 4b, and 5b exhibited increases in the PF indicator. Six ecological regions (3a, 4a, 4b, 5a, 5b, and 6c) exhibited increments in the NF indicator. NPF and DS indicators followed the same global trend as the regional scale, while the remaining indicators (DF, RA, VA, YS, MOS, CS, MS, DC, and OC) exhibited irregular variations that could be mainly explained by drivers in each ecological region. High variability was observed in ecological region 6c in terms of indicators DF, VA, RA, and DS.

Figure 3 illustrates some of these changes through a map of forest cover type criteria and related indicators that were extracted from 1985 and 2005 imagery. A pattern that was characterized by brown segments from agriculture activities was apparent in the centre of the image. A decline in coniferous forest (in dark green) was also noticeable throughout the entire territory after 1985 and is representative of the territory under study.

Error estimation of variation in areal proportions between 1985 and 2005

Error estimates of variation in areal proportions, which used Equation (3), have been summarized by indicator as error means and standard deviations across the six ecological regions (**Figure 4**). Indicators of criterion 1 had the lowest means and standard deviations, suggesting the highest accuracy and precision of these indicators. Indicators of criteria 2–4 showed overall increasing absolute values for their respective means and standard deviations, particularly for indicators RA, DS, DC, and OC. These levels of error (frequently below 5%) were related not only to the confusion matrix terms but also to the proportion of area that was occupied by a given indicator.

The adjusted versus initially classified changes in areal proportions of indicators for the ecoregions and for the AT–NQ region have been summarized in **Figure 5**. These changes were used to assess the effects of errors on the change trends described previously. Overall, the sign associated with the changes remained the same after adjustment, except for a few cases that usually remained close to the origin. The absolute value of change after adjustment was about half that of the classified value, as indicated by the slope of the linear regression fitted to the data in **Figure 5** ($b_1 = 0.52$, AT–NQ; a similar regression was found for ecological regions). As a consequence, the results reported for the aforementioned indicator trends remain mostly valid, except that the magnitude of change is lower by half on average than that reported for the classified indicators.

Discussion

Classification and validation methods

The ECM that was proposed in this study was efficient overall in quantifying four criteria in a large-area mapping project that otherwise encompassed a wide diversity and complexity of forest conditions. This method emphasized the critical expertise of a remote sensing analyst, but it also involved a substantial level of subjectivity in the process. Therefore, specialists who are trained in forest mapping and possess an extensive knowledge of the territory are crucial to the success of this classification method. Instead of being used as training sets in supervised approaches, few additional datasets were required in this study for calibrating and validating our class and indicator labelling process. A number of studies have shown that ECM has great value for large-area mapping projects using medium- and coarse-resolution remote sensing data (Cihlar et al., 1997; Beaubien et al., 1999; Peddle et al., 2004; Théau et al., 2005; Boudreau et al., 2008; Olthof et al., 2008; Fraser et al., 2009; van Lier et al., 2011). In particular, the circa 2000 EOSD land cover map of Quebec, which was produced with ECM, showed an overall accuracy in the 75%–80% range and has been used by many end-users. Although land cover maps that have this level of detail over a large area are not routinely produced, they should be used and validated as baselines for the monitoring of C&I for SFM across large stretches of boreal forest.

Nevertheless, analysis of the sources of classification errors showed that most errors could be attributed to a few individual classes due to spectral confusion between similar indicators (DS versus VA and RA, for example). Consequently, small and (or) narrow patches of some indicators were ignored by the ECM classifier when they were smaller than 1 ha because of the modal filter (90 m $\times$ 90 m) that had been applied, often to fragmented forest landscapes. In addition, ECM is performed only on individual pixels and does not consider the spatial context (i.e., pattern), unlike object-oriented classification (Desclée et al., 2006). Indeed, ecological regions with larger homogenous patches were more precisely mapped in this study. A thorough study of the spatial patterns of change in relation to error levels should be performed to fully assess the advantages and limitations of ECM for change detection beyond the usual pixel-level error characterization.

Finally, a group of error sources that are often underestimated relates to the reference data sets that are derived from photo-interpretation of high resolution

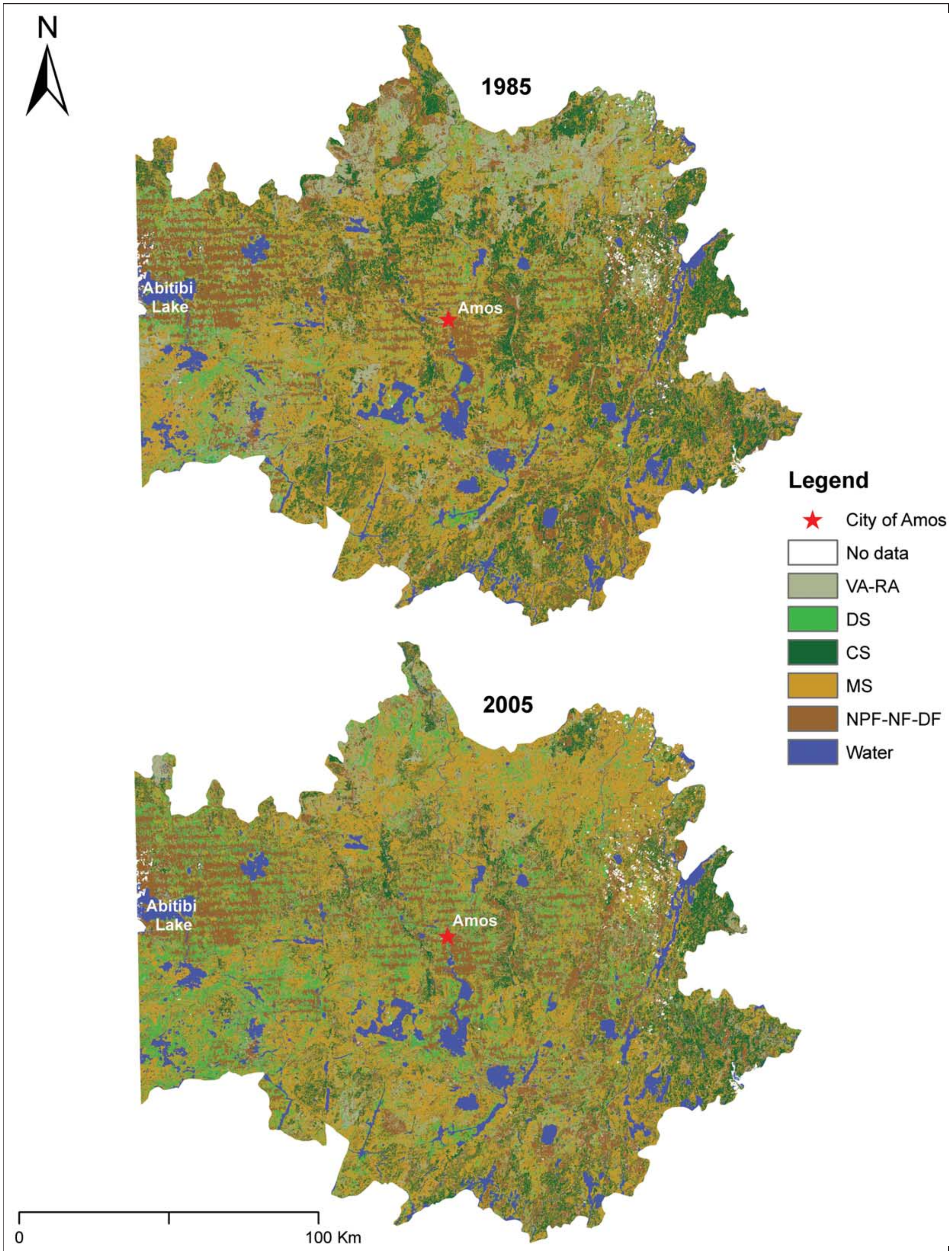

Figure 3. Forest cover types criterion in ecological region 5a between 1985 (top) and 2005 (bottom) imagery.

imagery and which are used to validate the classification. An important one is the mismatch between the 1 ha square central area and classified 30 m Landsat pixels, given the 10–20 m RMS positional error of the latter. Variation in the conditions of airborne imagery acquisition was found to be another significant source of error in the photo-interpretation process, including variable day and time-of-day-induced changes in tree shadow proportions and atmospheric disturbances (e.g., light haze with decreasing image contrast). Finally, the common presence of

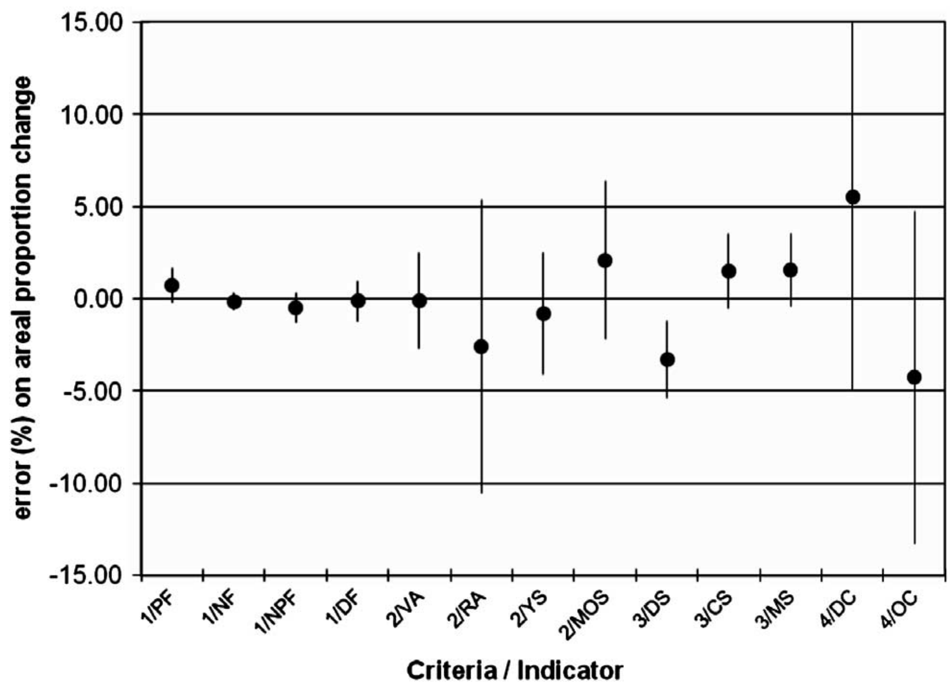

Figure 4. Error statistics on the changes in areal proportions of indicators (means and standard deviations across six ecological regions).

two classes within the central 1 ha area frame that was due to forest heterogeneity often induced increased variability between the three photo-interpretation results. Indeed, about 50% of the time, the third interpretation was needed to make a final decision. Overall, Foody (2010) showed that even small errors in reference data can introduce significant errors into post-classification change detection. Usually, a conservative bias results from such error, as described in Verbyla and Hammond (1995).

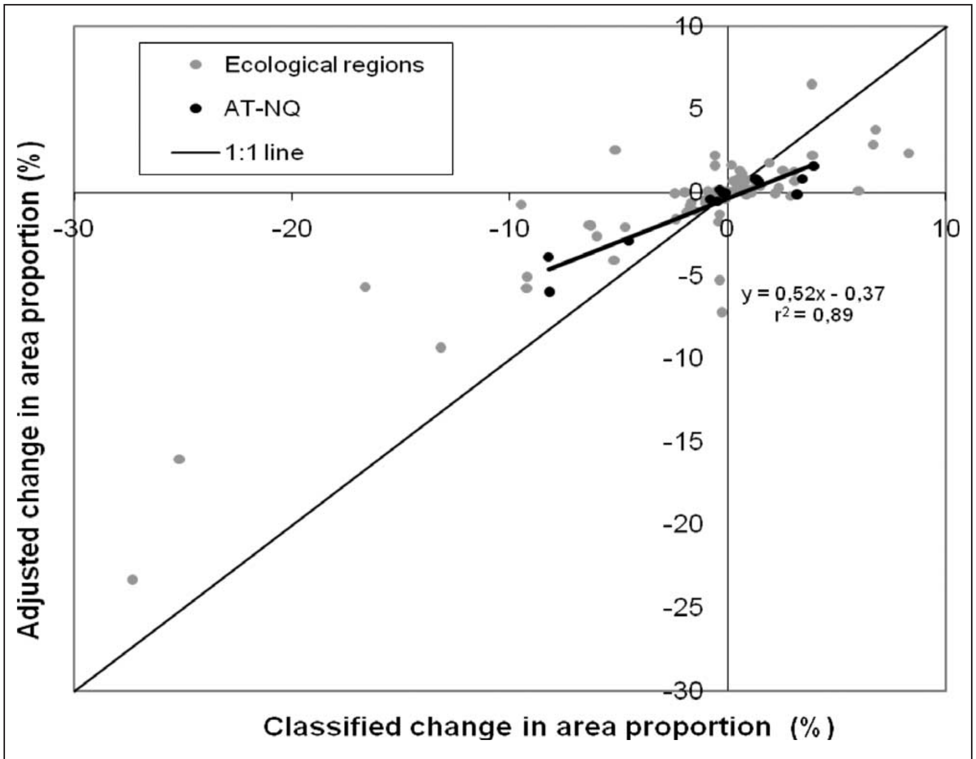

Figure 5. Adjusted versus classified change in areal proportions of indicators for ecological regions and the entire AT–NQ region, according to Equation (3).

Changes in the state of the forest

The forest is a living and dynamic entity subject to several natural and anthropogenic processes that shape it. Monitoring that uses four criteria to better understand the development of the forest and identify trends that will contribute to better management of this resource is essential. Taking into account classification errors, the changes that were observed over 20 years (1985–2005) showed a decrease in CS, MOS, and DC indicators. These changes may be explained by drivers that modified the state of the forest during this period. At the same time, increases were observed in NPF, VA, RA, DS, and OC. Wildfires and forest management activities (mainly harvesting and roads) were the major drivers that were documented for this territory (Bergeron et al., 2004).

Our results show that forest cover type criteria are consistent with other studies, which have found that CS has been continually declining since 1975 (MRNF, 2002, 2004). Over twenty years, wildfire has affected 65 992 ha, while harvesting has affected 91 744 ha; together, the two disturbances account for more than 157 736 ha and may explain the observed declines in PF indicator and forest changes.

Other drivers have been reported for ecological region 4a, including insect outbreaks. Chief of among these, prior to 1980, is the spruce budworm *Choristoneura fumiferana* (Clemens). As it is likely that the medium-term effects of spruce budworm were already visible in 1985, they have not reported here as important drivers. Finally, because climate change effects on forest are related to changes in the frequency and severity of fires, drought, pests, and diseases, they were not commented on in this study. Nevertheless, other phenomena related to the observed changes could be associated with the increase in the growing season or annual mean temperature in recent decades (0.5 °C in 1985 and 1.0 °C in 2004[1]) and could have favoured the establishment of intolerant species. They may also explain gains in DS and early stage of development (VA, RA) indicators. Other secondary drivers like wetlands and mining activities were not reported because of the lack of documentation for this territory.

The decrease in DC was concomitant with the drop in cover of the MOS indicator. Major drivers such as logging and fire during the study period are thought to be responsible for the decline in CS and MS and the increase in early developmental stages (VA, RA) and OC. This response is consistent with that reported by Bouchard and Pothier (2010), where contemporary disturbance rates, including those for both logging and fire, have gradually become higher than the fire rates observed during the pre-industrial period. This effect may also be explained by the characteristics of the northern region, where black spruce boreal forest is more open and less productive, and the recovery time may be longer than in the more productive southern region, where mixedwood stands dominate. Also, recent research suggests that partial harvesting in lowland black spruce stands may increase the rate of paludification, i.e., the development of a thick, waterlogged forest floor layer that reduces stand productivity (Fenton and Bergeron, 2007).

The classified Landsat images illustrated that the average area burned by wildfires was lower in the period prior to 1985 compared to 2005. For instance, the Val-Paradis wildfire (noticeable in the western part of ecological region 6a) resulted in a reduction of 12 557 ha of mature mixed wood boreal forest (Hely et al., 2003). The 2005 spectral signatures from the burned area of Val-Paradis showed some progression to other indicators in early stages of growth. Yet, most of the area still lacks an advanced stage of revegetation. Ecological region 4a had the highest increase of DC (40.5%), in contrast to the general trend observed (**Table 5**). About 12% of this region is covered by agricultural lands. In the late 1980s, many agricultural lands were abandoned in the territory (Gachet et al., 2007); by 2005, these abandoned lands were colonized by high and dense shrubs and trees.

Based on a closer examination of forest cover type change maps for region 5a (**Figure 3**), some of the documented changes are thought to be real and some were obviously due to classification errors; additional investigations are needed to clearly sort them out, especially considering the limitations of post-classification change detection approaches using a complete transition probability error model such as that proposed by Hall et al. (1991). Forested areas in early stages of growth such VA, RA, and YS indicators contributed significantly to the misclassification of deciduous stands in 2005 because of their spectral similarity to the DS indicator. Sivanpillai et al. (2005) found that, when medium-resolution satellite data such as Landsat were used for mapping forest cover, vegetated areas within an urban environment (parks, wooded areas) were often misclassified as forest.

This study focused mainly on the extraction of change indicators in the target regions without distinctions being made regarding the nature of these changes and on an areal basis, rather than on an aggregated pixel-by-pixel basis. Thus, it could be very useful to address the problem of change type classification inside the procedure itself. The overall accuracy of criteria ranged from 58% to 83%, which was relatively high compared with conventional provincial inventory methods (Coulombe et al., 2004) and is believed to be conservative because of the use of photo-interpreted high-resolution imagery (Verbyla and Hammond, 1995). Unfortunately, we were not able to compare our multi-dataset Landsat classification of 20 years to another large area inventory, such as the provincial inventory, because territory limits are quite different and there is a lack of direct correspondence between indicators to be compared (MRNF, 2004).

[1]Source: http://www.climat-quebec.qc.ca/

Such information derived from indicators regarding the dynamics and spatial distribution of forests is clearly useful for assessing their health and for modelling environmental processes such as carbon sequestration (Foody et al., 1996, Wulder et al., 2004). In addition, this study showed an increasing need for continuous mapping and monitoring changes of AT and NQ land cover through the implementation of a long-term, low-cost, and high-quality forest remote sensing monitoring program. Indeed, this approach has been applied for operational purposes at a 5 year interval (not reported here) to monitor the state of the forest as a complement to, and at a faster rate than, available conventional forest inventories described above (Gillis et al., 2005; Valeria et al., 2008).

Conclusions

The ECM that was used in this study, and which was applied to multitemporal Landsat normalized mosaics, proved to be effective in providing a quantitative assessment of the areal change, by region, of key selected indicators in the eastern Canadian boreal forest. An overall accuracy ranging from 58% to 83%, thought to be conservative, was achieved using a classified Landsat dataset covering 20 years, with resulting conservative errors to areal change statistics most of the time.

Standard multispectral satellite images at 30 m resolution, such as those offered by Landsat, have considerable value at low cost for mapping changes in some of the key environmental and sustainable forest management indicators in large boreal forest areas such as the AT and NQ regions. Moreover, some of these indicators (PF, NF, MOS, MS, and DC) showed a precision greater than 60% producer accuracy and an error frequently below 5% of the variation associated with areal proportions. The aforementioned sources of errors were partly accounted for by utilizing the confusion error matrix that was used to correct the proportion of each indicator by region of interest (Hall et al., 1991). Our analysis particularly showed the limitations of ECM within a post-classification change analysis approach for the monitoring of DF, VA, RA, YS, and DS indicators from Landsat imagery.

Overall, our results are consistent with those provided by other large area inventory efforts that have documented a continuous modification of the boreal forest in Canada, i.e., an increase in the cover of young regenerating and deciduous stands and a significant decline in the cover of CS and MS (Coulombe et al., 2004). The quantitative change in each indicator, when corrected for classification errors, reveals a slight decrease in the area of productive forest, a shift in cover type, and a decrease in the cover of coniferous stands, which is driven by harvesting activities and wildfire. Coniferous, mature, and dense stands are essential habitat for many boreal species and are more valuable for the forest industry across the region.

These results demonstrate that medium-resolution (30 m) remote sensing tools can be used to monitor at low cost the state of the boreal forest in AT and NQ. These tools can also produce key indicators extracted from Landsat imagery, as long as error levels are reported along with areal change statistics to assess the strengths and limits for the various indicators. This study showed that, through the extraction of key indicators, the bi-temporal classified satellite imagery can be used as an independent assessment tool to provide the public and government with up-to-date and complementary information on the state of the forest. Such information could be derived from multitemporal Landsat imagery or similar data sources. It could allow decision makers, the general public, and various forest users to be aware of and to understand the location, nature and origin of key forest changes over time on a regular basis and in a simple and easy-to-understand manner.

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